DESIGNING INTERVENTION STRATEGY FOR PUBLIC-INTEREST GOODS

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By
Ece Zeliha Demirci
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We certify that we have read this dissertation and that in our opinion it is fully adequate, in scope and in quality, as a dissertation for the degree of Doctor of Philosophy.

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ABSTRACT

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Public-interest goods, which are also referred as goods with positive externalities, create benefits to individual consumers as well as non-paying third parties. Some significant examples include health related products such as vaccines and products with less carbon emissions. When positive externalities exist, the good may be under-produced or under-supplied due to incorrect pricing policies or failing to value external benefits and that is why a need for intervention arises. A central authority such as government or social planner intervenes into the system of these goods so that their adoption levels are increased towards socially desirable levels. The central authority seeks to design and finance an intervention strategy that will impact the decisions of the channel in line with the good of the society, specified as social welfare. A key issue in designing an intervention mechanism is choosing the intervention tools to incorporate. The intervention tools can target the supply or demand of the good. One option for the intervention tool is investment in demand-increasing strategies, which affects the level of stochastic demand in the market. Second option is investment in strategies that will improve supply of the good. Alternatives for this option include registering rebates or subsidies and investment in yield-improving strategies when production process faces imperfect yield.

As several real life cases indicate, central authority operates under a limited budget in this environment. Thus, we introduce and analyze social welfare maximization models with the emphasis on optimal budget allocation. We model the lower level problem, which represents the channel as a newsvendor problem. We then utilize bilevel programming for modeling the environment incorporating the role of central authority. After obtaining single level equivalent formulations of the problems, we analyze and solve them as non-linear programs.

Our first problem is to analyze an intervention strategy, which uses only subsidy issued per unit order quantity. We explore the subsidy design problem for single retailer and n retailers cases. We show that all of the budget will be used under mild conditions and present structural results. Also, we analyze subsidy design problem for two echelon setting, where the central authority gives subsidy both to retailer and manufacturer. We consider centralized and manufacturer-driven problems and present numerical results.

In the remaining part of the thesis, we focus on joint intervention mechanisms in which two intervention tools are applied simultaneously. First, we study a joint mechanism composed of demand-increasing strategy and rebate. We present two models and associated structural properties. First model aims to find optimal budget and allocation of it among intervention tools. We deduce that rebate amount may be independent of investment made in demand-increasing strategies and improvement pattern of demand. Second model decides on the optimal allocation of a given budget between intervention tools. We show that central authority will allocate all budget under mild conditions. Furthermore, we use real-life data and information of California electric vehicle market in order to verify the proposed models and show benefits of taking such an approach. We also explore the application of the joint mechanism under a given budget for exponentially distributed demand family and fully characterize the optimal solution. The analysis of the solution reveals that designing an intervention scheme without considering an explicit budget constraint will result in budget deficit and excess money transfers to the retailer. As the second modeling environment we consider a joint mechanism consisting of demand-increasing strategy and yield-improving strategy in a setting where yield uncertainty exists. We introduce lognormal demand and yield models that take into account the investments made for improving them. We test the suggested model with a case study relying on the available estimates of US influenza market. The results indicate that addressing both demand and yield issues by the proposed mechanism will increase vaccination percentages remarkably.

Keywords: Public-interest good, Intervention, Rebate, Subsidy, Demand-increasing strategy, Yield-improving strategy, Newsvendor problem, Case study, Bilevel programming.

ÖZET

KAMU YARARINA OLAN ÜRÜNLER İÇİN TEŞVİK MEKANİZMASI TASARIMI

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Literatürde olumlu dışsal yararı olan ürünler olarak da bilinen kamu yararına olan ürünler kullanımı arttığında kullanan dışındaki kişilere de yararı olan ürünlerdir. Salgın hastalıklara karşı yapılan aşılar ve düşük karbon emisyonu üreten ürünler bilinen önemli örneklerdendir. Olumlu dışsal yararın olduğu durumlarda yanlış fiyat politikaları ve ürünün faydalarının göz ardı edilmesi ürünlerin gereken miktarda üretilememesi veya tedarik edilememesine yol açmakta ve bu durum bu tip sistemlere müdahale edilmesi gereksinimini doğurmaktadır. Devlet veya uluslararası kar hedefi gütmeyen organizasyonlar gibi merkezi bir otorite bu sistemlere ürünlerin kullanım seviyelerinin toplumsal istenen seviyelere yükseltilebilmesi için müdahale eder. Merkezi otoritenin amacı tedarik zincirine toplum yararına karar verdirmeyi sağlayacak bir müdahale stratejisi tasarlamak ve finanse etmektir. Müdahale mekanizması tasarlarken önemli noktalardan biri kullanılacak müdahale tiplerine karar vermektir. Müdahale tipleri ürünün arz veya talebini etkileyebilir. Talep artırıcı stratejilere yatırım yaparak pazardaki rassal talep seviyesini etkilemek müdahale tiplerinden biridir. Ürünlerin arzını etkilemek ise bir diğer müdahale tipidir. Bu müdahale tipi için seçenekler indirim, teşvik vermek veya verimi iyileştirici stratejilere yatırım yapmayı içerir.

Gerçek hayat uygulamaları, merkezi otoritenin kısıtlı bir bütçe altında sisteme müdahale ettiğini göstermektedir. Bundan yola çıkarak bütçe planlamasını eniyilemeyi hedefleyen sosyal refah enbüyültme problemleri geliştirdik. İki seviyeli programlama yöntemini kullanarak geliştirdiğimiz modelleri tek seviyeli doğrusal olmayan modellere indirgedik ve analiz ettik. Alt seviye problemleri gazeteci çocuk problemi olarak modelledik.

Öncelikle sadece sipariş miktarı başına verilen teşvikten oluşan bir müdahale stratejisini analiz ettik. Bu problemi tek perakendeci ve n perakendeciden oluşan sistemler için inceledik ve bütçenin tamamının normal koşullar altında kullanılacağını gösterdik. Daha sonra bu problemi merkezi otoritenin hem perakendeciye hem de üreticiye teşvik verdiği iki kademeli tedarik zinciri için inceledik. Merkezi ve üretici odaklı durumlar

için sayısal analizler yaptık.

Tezin geri kalan kısmında, aynı anda iki müdahale tipini uygulayan bütünleşik müdahale tasarımı üzerine çalıştık. İlk olarak, talep artırıcı strateji ve indirimden oluşan bütünleşik bir mekanizma önerdik. Bu mekanizma için iki karar modeli ve analitik sonuçları sunduk. İlk model eniyi bütçe miktarını ve bütçenin müdahale tiplerine paylaşımını bulmayı amaçlar. Bu model için indirim miktarının talep artırıcı stratejilere yapılan yatırımdan ve talebin iyileşme şeklinden bağımsız olabileceğini gösterdik. İkinci model belirli bir bütçenin müdahale tiplerine paylaştırılma şekline karar verir. Belirli koşullarda merkezi otoritenin bütün bütçeyi kullanacağını gösterdik. Ayrıca, Kaliforniya elektrikli otomobil pazarının verilerini kullanarak geliştirdiğimiz modeli test ettik ve faydalarını gösterdik. Daha sonra bu mekanizmayı özel bir durum için analiz ettik ve eniyi çözümü tanımladık. Eniyi çözümün analizi bütçe kısıtı dikkate alınmadan tasarlanan müdahalelerin bütçe açıklarına ve perakendeciye fazla para akışı yapılmasına neden olacağını göstermektedir. İkinci olarak, üretim veriminde belirsizliğin olduğu sistemler için talep artırıcı ve verimi iyileştirici stratejilerden oluşan bir bütünleşik mekanizma önerdik. Lognormal talep ve verim modelleri geliştirdik. Önerdiğimiz bu modeli Amerika grip aşısı pazarı verileriyle test ettik. Sonuçlar, talep ve verimi iyileştirmeyi hedef alan müdahale mekanizmalarının aşılama yüzdelerini önemli ölçüde iyileştirdiğini göstermektedir.

Anahtar sözcükler: Kamu yararına ürün, Müdahale, İndirim, Teşvik, Talep artırıcı strateji, Verimi iyileştiren strateji, Gazeteci çocuk problemi, Vaka analizi, İki seviyeli programlama.

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Chapter 1

Introduction

1.1 Motivation and Objective

Public-interest goods, which are also known as goods with positive externalities, benefit consumers in addition to non-paying third parties. Health related products such as various medicines and vaccines, energy efficient appliances, eco-consumables, and products with less carbon emissions are some well-known examples. Specifically for instance, vaccines obviously make the individuals less susceptible to a contagious disease and also they reduce the chances that non-vaccinated people will get the disease. Clearly, vaccination is good for the whole society since with only few unvaccinated individuals the transmission of the disease cannot be maintained and the risk of pandemics will be low. Similarly, with electric vehicles, the reduction in transportation-related air pollution and climate change emissions compared to conventional vehicles will benefit owners of these vehicles and also provide considerable benefit to other people. In a free market, this type of goods are either under-consumed or under-produced due to incorrect pricing policies or neglecting the external benefits. Thus, there is a need for regulating this type of goods' environment by a central authority (government or social planner) so that their consumption is raised towards socially optimal levels. Here, the main goal of the central authority is to design and fund an intervention scheme that encourages the channel to choose decisions for the benefit of the society.

A critical issue while designing an intervention mechanism is how it should be incorporated into the system. It can be introduced at different levels of the system by allocating available budget among investment alternatives. One alternative is making investment in demand-increasing strategies. We assume that this investment is devoted to any attempt that will promote the consumption of these goods in the medium to long run. In practice, the strategies can be advertising, organizing education and awareness campaigns, and expanding access to this type of goods. Another alternative is to invest in strategies that will improve system operation. Options for this alternative include administering incentives in the form of rebates (i.e. refund of money awarded to consumers of that particular product) or subsidies (i.e. payment to the firm that manufactures and/or sells the product for every unit produced/ ordered) in order to improve good's availability, and initiating research and development to improve the production process when imperfect yield and/or yield uncertainty arises inherent to the environment.

Several rebate schemes have been introduced in practice to encourage usage of these goods. For instance, a large number of national and local governments have initiated government incentives to foster sales of electric vehicles. US government provides federal income tax credit benefits up to $7500 [1]. Besides federal policy, several states have been implementing incentive programs. One example is California, which offers a rebate up to $5000 in addition to federal tax credit. Germany also subsidizes electric vehicle sales by providing a rebate of €4000 for all electric vehicles and €3000 for a plug-in hybrid electric vehicle [2]. Another example is that several tax credit and rebate programs have been established by federal, state, and local governments in US for homeowners to switch to renewable energy such as solar panel systems or energy efficient projects [3].

Analysis of intervention through subsidies or rebates is also common in the literature, especially for public-interest goods. For example, Raz and Ovchinnikov [1] consider these types of intervention tools for a general class of public-interest goods; Mamani et al. [2] consider a subsidy program to achieve optimal vaccine coverage,

[1] http://www.fueleconomy.gov/feg/taxevb.shtml
[2] https://www.theguardian.com/world/2016/apr/28/germany-subsidy-boost-electric-car-sales
[3] http://www.solarcity.com/residential/solar-energy-tax-credits-rebates

and Lobel and Perakis [3] consider subsidies to achieve a desired adoption target for solar photovoltaic technology. The reason behind giving incentives to channel is to make the goods acceptable to customers and viable to buy, and thus to enable their wider adoption.

Subsidies and rebates are generic tools used for regulating the usage of public-interest goods, so we start our analysis by considering intervention mechanisms only composed of subsidies in different settings. However, considering more than one strategy simultaneously has not been well studied. Joint mechanisms composed of two intervention tools; demand-increasing strategies and rebates or demand-increasing strategies and research and development are firstly introduced and analyzed in this thesis. For joint mechanisms, the problem of central authority is to decide on the optimal allocation of available budget among two investment alternatives.

Public-interest goods such as new medicines, energy efficient appliances or eco-consumables are new goods and technologies, so they face highly uncertain demand. Decisions on incentives and regulations are taken depending on incomplete or incorrect information on demand, good's performance or future technology advances. Additionally, the intervention is implemented until the good under consideration is made acceptable to customers and its effectual adoption is ensured. Thus, considering the demand uncertainty and implementation horizon, we formulate a newsvendor model for the retailer (or manufacturer, depending on the setting under consideration). Moreover, based upon real world applications central authority needs to consider the available budget amount (or optimal budget) while determining the intervention scheme. So, we develop models that decide on how to allocate budget among intervention tools in public-interest good environment. We also find out structural results that facilitate solving the models.

1.2 Scope and Research Questions

The research presented in this dissertation aims to provide a unifying framework for designing intervention mechanism for a general class of public-interest goods. We use this framework to propose a strategy for ensuring wider adoption of the goods in different settings, i.e. single echelon and two echelon systems, with different intervention tools. We introduce models, which enable decision makers to take right decisions with the available information and allow one to measure the outcomes in terms of budget and utility. We also construct case studies relying on real life data in order to illustrate the positive impacts of using proposed mechanisms and present comparisons with respect to current policies and status.

Specifically, the following research questions are posed in this thesis:

- Generalized formulation to determine subsidy amount to be offered for stochastic exogenous demand
  - Can we identify a structure for the optimal solution?
  - Can we identify additional structural properties?
- Generalized formulation to design intervention scheme with incentive-sensitive demand
  - Different environments are considered.
  - Can we identify structure or structural properties for the optimal solution?
  - What would be the impact of applying proposed intervention scheme on real world cases?

In this thesis, we use bilevel programming to model the framework explained. A bilevel programming problem is a hierarchical optimization problem that includes two levels of optimization problems within a single formulation, one of which becoming part of the constraints of the other one. To summarize, an upper-level decision maker or leader makes his optimal choice first and then a lower-level decision maker or follower makes his decision by optimizing own objective function given the dominant player's action. A distinguishing property of this programming is that each player's decision is affected by the other's decision, but not completely controlled by it [4, 5]. For our models, the leader is the central authority with the objective of maximizing social welfare and the follower is a retailer or a manufacturer whose problem is modeled in a newsvendor setting.

From a general point of view, there are several contributions of the thesis. The first one is modeling a newsvendor environment with welfare implications via bilevel programming. Note that the modeling structure used is quite general in the sense that it can be modified for alternative intervention schemes. Using the modeling framework, we derive analytical results that will generate insights for policy makers as well as ease the procedure to find an optimal solution. Moreover, we construct two case studies based on real life data by using novel calibration approaches. We utilize these case studies to validate our findings and show benefits of applying proposed schemes incorporating incentive-sensitive demand. Within these case studies, we propose concepts that play a critical role in evaluating decisions to be made. One of the ways to assess the performance of our approach is to make comparisons with results of benchmark models. Another important concept is expected excess budget, which measures the risk of decisions made. Lastly, we suggest a model that offers a coordination possibility for one of the schemes considered.

1.3 Outline

The remainder of the thesis is organized as follows. Chapter 2 summarizes related literature and provides a brief description of bilevel programming. In Chapter 3, we study the intervention problem in an environment in which the system is regulated by the power of subsidies. We firstly analyze basic cases, i.e. single echelon systems consisting of single retailer and n retailers, respectively. For both of them, we show that all of the available budget will be used under mild conditions. For the model with n retailers, the subsidies are allowed to be negative (i.e. tax) and thus the incentive mechanism imposes a pricing mechanism on the agents depending on their status. By this way, we allow for money transfers between central authority and retailers, and among retailers. We find out that under identical cost parameters but different utility functions, the subsidies allocated can be ordered according to marginal utilities. Next, we examine two echelon systems for centralized and manufacturer driven settings, in which central authority controls the system through the use of subsidies administered to both retailer and manufacturer. Regarding the centralized case, we find that centralized system turns out to be identical with single echelon system and the amounts of subsidies only affect the expected profit sharing between retailer and manufacturer.

Real life cases depict that intervention through only subsidy or rebate is not enough to ensure the good of society. For instance; several subsidy programs are under implementation to increase influenza vaccination rates in most of the developed countries. However, the resulting vaccination percentages are significantly lower than the targeted percentages [6, 7]. Thus, we consider joint mechanisms in the rest of the thesis. The joint mechanisms consist of two intervention tools: (i) investment made in demand-increasing strategies and (ii) investment made in strategies improving system operation. We investigate the joint mechanisms for a setting consisting of a central authority and a retailer or a manufacturer. In Chapter 4, we consider joint intervention mechanism composed of demand-increasing strategy and rebate. We introduce two models to determine utility maximizing intervention schemes when budget is optimized and budget is exogenous, respectively. Also, we further investigate the models to derive structural properties for the optimal solution. We present two decentralized approaches as benchmarks for both models. Finally, we conduct a case study for California's electric vehicle market and validate our findings by a detailed analysis of the results, including comparisons with the current practice. In Chapter 5, we extend the problem in Chapter 4 under the assumptions that demand is exponentially distributed and demand-increasing strategy has a constant effect on the mean demand. We characterize the optimal solution structure in terms of budget level and efficiency of demand-increasing strategy. In Chapter 6, we study the joint intervention mechanism in an environment that includes production yield imperfection as well as uncertainty. For this case, the joint mechanism includes demand-increasing strategy and research and development investment, which improves yield. We enrich this study by constructing a case study based on available information on US influenza vaccine market.

We conclude the thesis with a summary of results and future research directions in Chapter 7.

Chapter 2

Literature Review

This thesis focuses on supply chain of a public-interest good; hence it is closely related to two streams of literature: economics and operations management. We present a brief review of related studies from each stream in the following sections. The research problems that we address deal with sequential decision making in a hierarchical system with independent objectives. We utilize bilevel programming to model the hierarchical relationship between the decision makers. Hence, last section contains a description of bilevel programming framework.

2.1 Economics Literature

The economics literature has focused on policy design for regulating monopolies in the public-interest (see [8, 9] for further details). Subsidy, tax, and lump-sum transfers are frequently used as public policy instruments in welfare economics. The details on how they are used and their effects on the economy are discussed thoroughly in [10]. Moreover, the impact of intervention tools (such as subsidies and advertising) for accelerating the diffusion of a new product is investigated in the literature. In this context, government is concerned with maximizing the number of adopters while determining the intervention scheme. Here, the intervention tools directly affect the adoption level. On the other hand, in this thesis we study the intervention problem in a newsvendor setting, thus the tools are affecting the order quantity. Some examples from this stream of literature are: [11], [12], and [13]. Horsky and Simon [11] examine the effect of firm's advertising strategy on the adoption level of a new product, whereas Kalish and Lilien [12] study the problem of determining a time dependent subsidy scheme under a predetermined government budget. In a recent study, De Cesare and Di Liddo [13], innovation diffusion problem is examined for a Stackelberg game. The government chooses the subsidy amount given a predetermined budget, whereas the monopolist producer determines the pricing and advertising strategies.

Our approach considers a central authority with all available information. However, the effect of private information is well studied and understood in economics literature by studies on mechanism design. In mechanism design, a principal aims to optimize outcome of any organizational or market system composed of self-interested agents. It is assumed that agents act strategically and may have some private information. Within this context, the research question is that whether it is possible to design a mechanism that will induce efficient decisions maximizing total welfare and whether agents will participate in the mechanism. More detailed information about this field can be found in Myerson [14] and Jackson [15].

2.2 Operations Management Literature

Newsvendor problem is a part of problem settings that we analyze in this dissertation. This problem has been studied widely in the literature (see [16] for taxonomy of the literature so far). However, our settings have one more decision level (central authority) and exhibits interrelated decision hierarchy making the analysis of the problem more complicated. Also, on the contrary to traditional newsvendor problem where quantities correspond to production or order quantities, in our setting it corresponds to capacity investment decision.

The problems that we study are also related in part to supply chain contracting literature. A detailed review can be found in [17]. The problems in this context focus on the impact of incentives (such as rebates or revenue sharing) on the echelons in a newsvendor environment. For instance, Taylor [18], Dreze and Bell [19], and Aydin and Porteus [20] show the effectiveness of sales-rebates in different settings. Note that the studies in this context consider the profits of the echelons while designing contracts rather than social welfare or utility implications.

Although the problems considered in this thesis can be seen in various settings, studies that combine intervention and its effects on social welfare in a newsvendor setting are scarce. The studies consider intervention tools in the form of subsidies and rebates. The existing studies in the literature within this context can be grouped based on which products it can be applied.

A stream of studies in the literature has been devoted to designing social welfare maximizing interventions for influenza vaccines in particular. The setting of this good is distinguished from the others due to characteristics of production process. Environment bears long production times, reformulation of vaccine composition each year, and yield uncertainty risk. The inefficiencies of a vaccine supply chain emanating from operational issues on the supply side and negative externality effect on the demand side mostly have not been addressed concurrently in the existing studies. A group of studies focus on only supply uncertainty and its impact on social welfare. Chick et al. [21] present first integrated supply chain/health economics model for a system consisting of a monopolistic manufacturer that sells vaccines to a government. Based on their results they investigate that manufacturer bears all of the production risks due to lack of coordination, which results in shortfall of vaccines. Hence, they derive a variant of cost sharing contract, which provides an incentive to the manufacturer to produce social optimum quantity. In Chick et al. [22], the major concern is to design a contract that will align incentives of government and manufacturer as in Chick et al. [21], but they consider an environment with asymmetric information about production uncertainty and include the possibility to fulfill the shortfall demand at a higher cost after the delivery date. Mamani et al. [23] extend the study of Chick et al. [21] to a scenario with multiple governments and risk of disease transmission across borders. They design a contractual agreement among governments that will enhance global health outcomes. Using a Cournot competition model, Deo and Corbett [24] argue that the limited number of entrants in a vaccine market, vaccine undersupply and low society surplus can be explained by yield uncertainty inherent to this environment. In all of these studies demand is exogenous to their models; however the consumer behavior (reflecting negative network externality effect) is also incorporated in this context more recently. Briefly, they assume that consumers' decision of whether to uptake vaccine depends on the vaccinated fraction of the population. Mamani et al. [2] show that in an oligopolistic vaccine market, a fixed subsidy should be administered to consumers so that a socially optimal immunization rate can be reached. However, they ignore the impact of yield uncertainty on the subsidy design and social welfare. Later, Adida et al. [25] study a similar problem in a setting that includes consumer behavior as well as yield uncertainty, and show that a fixed two-part subsidy scheme is not sufficient to coordinate even the monopoly market. They propose a two-part menu of subsidies that includes a subsidy dependent on coverage level given to the consumers and a unit production payment to the manufacturer in order to eliminate the market inefficiencies. In contrast to previous studies, Arifoglu at al. [26] do not formalize the setting as an incentive design problem, but instead explore the implications of demand side versus supply side interventions on the manufacturer's decision and societal outcome under different conditions. Regarding health related products, Taylor and Xiao [27] study design of subsidies from the perspective of a donor with a budget constraint for improving the availability of malaria drugs. The authors show that the optimal subsidy scheme of donor should include only purchase subsidy (i.e. optimal sales subsidy should be zero).

There is a growing literature dealing with implications of incentives on sustainability. Atasu et al. [28] study the design of e-waste take-back legislation considering two alternative policies. One is tax-based legislation and the other is legislation enforcing manufacturers a certain take-back rate. Here, tax corresponds to a negative subsidy per unit of sales. They analyze the impacts of both policies on manufacturers, consumers, and social welfare, and identify policy preferences. Krass et al. [29] and Drake et al. [30] both address the technology choice problem under emissions regulation. In particular, Krass et al. [29] study the effect of environmental taxation, subsidies, and rebates on the technology choice of a monopolistic firm. They study the problem as a Stackelberg game: regulator being the leader and profit maximizing firm being the follower. The firm faces deterministic price dependent demand and has to choose from technology alternatives that produce varying levels of emissions. In response to regulator's environmental policy, firm decides on the technology, production quantity, and price. Drake et al. [30] examine the technology choice and capacity decisions of a firm under both emission tax and cap and trade regulation. In contrast with Krass et al. [29] that consider multiple technologies, Drake et al. [30] consider two technology types having different emissions intensities.

The closest papers in this context are [1] and [31] in terms of analyzing welfare implications in a newsvendor environment. Our newsvendor setting differs from these studies in that they present a price-setting newsvendor model, whereas we either use stochastic exogenous demand or assume that demand distribution changes based on investment made in demand-increasing strategies. Raz and Ovchinnikov [1] study the government incentive design problem for a general class of public-interest goods. They consider an environment composed of a price-setting newsvendor firm and a government whose goal is to maximize social welfare, which in their model has four components: newsvendor firms profit, consumer surplus, externality benefit, and governments cost. The government coordinates the system with two types of intervention tools: (i) rebates (payments to consumers) and (ii) subsidies (payments to the newsvendor firm). They analyze three different mechanisms to coordinate the price and/or quantity: two simplified mechanisms that are only composed of rebates or subsidies, and a joint mechanism that consists of both rebates and subsidies. They show that joint mechanism can coordinate the system, whereas simplified mechanisms can coordinate either price or quantity. They also show that the coordinating solution leads to positive rebate and a negative subsidy (actually a tax) unless the externality is small. The authors examine the effectiveness of rebates compared to subsidies for the adoption of public-interest goods, and find out that using a mechanism with rebates only results in lower welfare losses. Lastly, they conduct computational study based on industry data of Chevy Volt and compare the current policy with the proposed joint mechanism and analyze the effect of uncertainty and externality on the design of incentives and social welfare. They observe that consumers benefit from uncertainty in the market. The latter study, Cohen et al. [31] explore subsidy design problem for green technology adoption. The paper proposes a model to find optimal subsidy scheme that maximizes social welfare while meeting a certain adoption target level. The social welfare function considered composed of supplier's profit, a consumer surplus, and government expenditures. They show that ignorance of demand uncertainty blocks the desired adoption target level to be achieved. Moreover, they also validate their findings by a case study for Chevy Volt in the US market.

Basically, our thesis differs from the above-mentioned studies in three dimensions: (1) joint intervention mechanisms affecting both demand and supply of the good; (2) an explicit budget consideration on the intervention mechanism; (3) a relatively general social welfare function with an emphasis on optimizing the budget allocation problem; and (4) incentive-sensitive demand (not only dependent on price, but more general).

2.3 Methodology: Bilevel Programming

Bracken and McGill are the first to study bilevel programming in three consecutive papers [32, 33, 34] presenting applications in the field of defense, production and marketing. In these early studies, bilevel programming is referred as mathematical programs with optimization problems in the constraints. Later, the designation bilevel and multilevel programming is first used by Candler and Norton [35]. Multilevel programming facilitates to model decision making process in a hierarchical system with multiple decision makers. It is an extension of bilevel programming to more than two decision levels. Particularly, bilevel programming formulation contains two levels of optimization problems, one of which is embedded in the constraints of the other one. From hierarchical system point of view, the levels operate sequentially and that is why lower level decision maker's problem (leader) becomes part of the constraints of the upper level decision maker (leader). A key feature of bilevel programming is that each party optimizes their own objectives; however their decisions are affected by each other but not completely controlled. First, the upper level decision maker begins determining levels of decision variables in anticipation of lower level decision maker's reaction. Following, the lower level decision maker makes his choices. More detailed description of bilevel programming as well as solution methodologies and application examples can be found in [4, 5, 36, 37].

Bilevel programming is related to Stackelberg model in the game theory field. Specifically, in a Stackelberg model the leader takes into account the follower's reaction while choosing his optimal strategy. Note that Stackelberg model and bilevel programming are similar as both possess hierarchical structure. However, lower level problem of a Stackelberg model is an equilibrium instead of an optimization problem.

Several real-world problems that include nested decision hierarchy can be modeled utilizing bilevel programs. Successful application domains of the concept include revenue management (e.g. [38]), congestion management (e.g. [39, 40]), hazardous materials management (e.g. [41]), network design problems (e.g. [42]), energy sector (e.g. [43]), engineering problems (e.g. [44]), and principal-agent problem (e.g. [45]) [4]. Also, one can suggest that bilevel programs may serve as a reasonable option for modeling managerial decisions as they have bilevel nature in terms of influencing subordinate level and having independent objectives.

The general formulation of a bilevel programming problem can be expressed as follows [4, 5]:

$$\min_{x \in X} \quad F(x,y) \tag{2.1}$$

$$\text{s.t.} \quad G(x,y) \leq 0 \tag{2.2}$$

$$\min\nolimits_{y \in Y} \ f(x,y) \tag{2.3}$$

$$\text{s.t. } g(x,y) \leq 0 \tag{2.4}$$

The variables of the formulation can be grouped in two categories: $x \in X \subseteq \mathbb{R}^n$ corresponds to upper level variables, whereas $y \in Y \subseteq \mathbb{R}^m$ stands for lower level variables. The functions $F, f : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}^1$ are called the upper level and lower level objective functions, respectively. In a similar manner, $G : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}^p$ and $g : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}^q$ are vector-valued functions representing the upper level and lower level constraints, respectively.

Bilevel programs are categorized in sub-classes depending on the functional forms of F, f, G, g. These programs are inherently difficult to solve. Jeroslow [46] show that even the simplest sub-class, in which all functions are linear is NP-hard. Thus, mostly simpler cases, i.e. problems with linear, quadratic or convex objective functions and/or constraints have been studied. Extreme point approach for linear case, branch and bound, complementary pivoting, descent method, penalty function method, and trust region method are some significant solution techniques developed to solve bilevel programs [4, 5]. Primary approach for solving bilevel optimization problems is to replace the lower level problem by its KKT conditions or first order condition whenever it is convex. In this case, the resultant KKT system is added to the constraints of the upper level problem, which yields a single level reformulation of the problem with complementarity constraints. Then, this formulation can be solved using nonlinear programming techniques. The bilevel programming problems that we analyze throughout this thesis possess the convex lower level problem structure, hence we obtain their corresponding single level equivalent formulations and treat them as nonlinear programs. Note that the decisions of lower and upper levels are determined simultaneously in this case.

Chapter 3

Intervention by Incentives

The aim of intervention is to achieve results close to socially desirable levels. Incentive (i.e. subsidy or rebate) is the most commonly used tool for this interest, especially for public-interest goods. Incentives have both direct and indirect effects on the system's operations: the central authority regulates the price of the good by altering costs and consequently influences the quantity or service level provided.

We start our study by investigating environments in which the system is controlled by the power of subsidies given per unit ordered. Some examples from literature analyzing intervention including subsidies are Chick et al. [21], Taylor and Xiao [27], and Raz and Ovchinnikov [1]. Our main goal is to examine the subsidy design problem from a general point of view subject to a constraint on central authority's budget. We firstly analyze basic cases, i.e. single echelon systems composed of a single retailer and n retailers, respectively. Next, we examine two echelon systems for centralized and manufacturer driven settings, in which central authority intervenes in the system through the use of incentives administered to both retailer and manufacturer. Finally, we introduce a general formulation for single echelon case with incentive-sensitive demand, which will be elaborated in the forthcoming chapters of the dissertation.

3.1 Basic Model

We firstly introduce the basic model with a single retailer and we follow up with its extension consisting of n retailers.

The system consists of a single retailer and a central authority. The central authority takes the role of the leader with the objective of maximizing utility achieved by the order quantity choice of the retailer, i.e. $u(Q)$. We assume that utility function is concave with respect to its argument. On the other hand, retailer is the follower with the objective of maximizing expected profit. The retailer's problem is a typical newsvendor problem, which decides on the order quantity Q. The retailer observes random demand x, with pdf f and cdf F. We assume that there is an upper limit on the demand anticipated, which is denoted by D_{max}. The cumulative distribution function of demand is defined as follows:

$$F(x) = \begin{cases} 0 & \text{if } x \leq 0, \\ \int_0^x f(x)dx & \text{if } 0 < x < D_{max}, \\ 1 & \text{if } x = D_{max}. \end{cases}$$

The unit revenue of selling product is p and the unit cost of buying the product is c. Also, there is a salvage value s per unit of unsold products. Besides, central authority administers incentive, r, per unit ordered to the retailer, which is limited with a fixed budget amount, B. In the classical newsvendor problem the relations between the cost values are assumed as $p > c > s$. However, we allow for $c \geq p$ in our models.

The bilevel programming formulation of the problem is as follows:

Model BM-BLP:

$$\max_r \quad u(Q) \tag{3.1}$$

$$\text{s.t.} \quad rQ \leq B \tag{3.2}$$

$$\max_Q \mathbb{E}[P(Q)] \tag{3.3}$$

$$\text{s.t. } D_{max} \geq Q \geq 0 \tag{3.4}$$

where $\mathbb{E}[P(Q)] = \int_0^Q (px + s(Q-x) - cQ + rQ) f(x)\,\mathrm{d}x + \int_Q^\infty (p-c+r)Qf(x)\,\mathrm{d}x$ is the expected profit of the retailer.

In the model, (3.1) is the central authority's objective of maximizing utility and (3.2) is the constraint on the level of budget to be allocated to the retailer. Besides, the retailer's problem is part of central authority's constraints, which is given by (3.3) and (3.4).

Lemma 3.1 *The problem defined by (3.3)-(3.4) is concave with respect to Q, so it can be replaced by its first-order condition [5].*

Utilizing Lemma 3.1, the formulation is reduced to a single level formulation.

Model BM-SLP1:

$$\max_{r,Q} \quad u(Q) \tag{3.5}$$

$$\text{s.t.} \quad rQ \leq B \tag{3.6}$$

$$F(Q) = \frac{p-c+r}{p-s} \tag{3.7}$$

$$p-c+r \geq 0 \tag{3.8}$$

$$c-s-r \geq 0 \tag{3.9}$$

Consider the model given by (3.5)-(3.9). (3.7) is the first-order condition that the optimal order quantity should satisfy. Note that constraints (3.8) and (3.9) are added to guarantee that the right hand side of (3.7) is a well-defined probability, i.e. it takes values between 0 and 1. Also, note that the problem is well-posed, i.e., for any r the optimal solution $Q(r)$ is unique. From the leader's perspective, we have a model with an implicitly defined feasible region by the follower's problem. In other words, whenever r is chosen by the central authority, retailer only chooses the optimizer of the newsvendor problem. The central authority has control over r and an implicit control over the real price of the good and consequently the order quantity.

By using the condition on Q, $Q = F^{-1}\left(\frac{p-c+r}{p-s}\right)$, the model can be reformulated.

The reformulation is as follows:

$$\textit{Model BM-SLP2:} \qquad \max_{r} \quad z(r) = u\left(F^{-1}\left(\frac{p-c+r}{p-s}\right)\right) \tag{3.10}$$

$$\text{s.t.} \quad g(r) = rF^{-1}\left(\frac{p-c+r}{p-s}\right) - B \leq 0 \tag{3.11}$$

$$h(r) = -p+c-r \leq 0 \tag{3.12}$$

$$t(r) = -c+s+r \leq 0 \tag{3.13}$$

Now, we have a single level problem with a single decision variable. However, due to nonlinearity of objective function (3.10) and constraint (3.11), Karush-Kuhn-Tucker (KKT) conditions are necessary but not sufficient for optimality. But still we can utilize them to help us in characterizing the optimal solution.

According to KKT conditions, an optimal solution should satisfy the constraints (3.11), (3.12), and (3.13). Also, there must be multipliers λ_i, $i = 1,2,3$, corresponding to each constraint respectively, and they must satisfy the following set of equations:

$$\frac{\partial z(r)}{\partial r} = \lambda_1 \frac{\partial g(r)}{\partial r} + \lambda_2 \frac{\partial h(r)}{\partial r} + \lambda_3 \frac{\partial t(r)}{\partial r} \tag{3.14}$$

$$\lambda_1 \left[B - rF^{-1}\left(\frac{p-c+r}{p-s}\right)\right] = 0 \tag{3.15}$$

$$\lambda_2 [p-c+r] = 0 \tag{3.16}$$

$$\lambda_3 [c-s-r] = 0 \tag{3.17}$$

$$\lambda_1, \lambda_2, \lambda_3 \geq 0 \tag{3.18}$$

Proposition 3.1

a) There is a maximum budget value, $(c-s)D_{max}$, above which the budget constraint may not be active.

b) If $0 \leq B \leq (c-s)D_{max}$, the budget constraint will be always binding.

Proof is presented in Appendix A.1.

This result is quite intuitive. Since the dominant objective is to maximize utility, which is dependent on the order quantity, the problem becomes equivalent to the maximization of the order quantity. From the first-order condition, we know that the order quantity is increasing with the increase in r, so the central authority wants to allocate as much as possible from the budget. Thus, all of the budget will be used at the optimal solution in most of the cases.

This model is a simple one, indicating that a reasonable solution can be found for a given budget level. In this respect, the model can be seen as a simple version of the available studies in the literature with a given budget level. It nicely shows the effect of changing budget on the utility as defined.

3.2 Basic Model with n Retailers

In a decentralized supply chain, each member acts with respect to its self-interest and this brings inequality and disparity issues between the members at the same level. Especially for products or services that are for public-interest, this problem is significantly critical. Behaving with respect to self-interest, allows the ones with sufficient income to hoard the goods, while leaving the other ones worse off. In order to ensure equivalence between the members or to encourage a public-interest operation, a central authority's intervention might be needed.

In this setting, incentives are allowed to be negative. Positive incentives motivates to order more or to engage in activities. However, the implications of the negative incentives are totally the opposite. It can be regarded as charging tax or applying higher price to that specific party under consideration. The most vital implication of negative incentive in the system is that it increases the budget of the central authority to be allocated. Thus, more demanding parties can get more benefit of the budget of the central control mechanism. In other words, what this intervention mechanism does is imposing a pricing mechanism by allowing money transfer between central authority and retailers, and between retailers.

In this section, we concentrate on the extended setting of the basic model with n retailers. An example associated with this case can be given as allocation of influenza vaccines between countries. The problem is determining subsidies of different purchasers of influenza vaccines. Here, purchasers/retailers correspond to countries and central authority may correspond to World Health Organization. The decisions on subsidy amounts are important as they may lead to suboptimal allocation of vaccines between countries when the objective is to minimize global financial costs of influenza. Different countries have different economic sensitiveness to influenza outbreaks and different objectives. Moreover, large quantities of vaccines may be reserved for wealthier developed countries such as US and European countries. On the other hand, some countries are less capable of buying in bulk quantities. It is known that majority of influenza outbreaks were first detected in Southeast Asia, and then spread to other countries. Thus, different utilities would be obtained from different countries. With a similar reasoning, cost and price of the good may be different in different countries.

All of the assumptions and cost parameters are the same with the basic model and they are indexed from $1, \cdots, n$. Similar with the basic model, we assume that utility function, $u_i(.)$, is concave with respect to its argument for all retailers.

Model NBM-MLP:

$$\max_{r_i} \quad \sum_{i=1}^{n} u_i(Q_i) \tag{3.19}$$

$$\text{s.t.} \quad \sum_{i=1}^{n} r_i Q_i \leq B \tag{3.20}$$

$$\max_{Q_i} \mathbb{E}[P_i(Q_i)] \tag{3.21}$$

$$\text{s.t. } D^i_{max} \geq Q_i \geq 0 \;\; i = 1, \cdots, n \tag{3.22}$$

where $\mathbb{E}[P_i(Q_i)] = \int_0^{Q_i} (p_i x_i + s_i(Q_i - x_i) - c_i Q_i + r_i Q_i) f_i(x_i)\,\mathrm{d}x_i + \int_{Q_i}^{\infty} (p_i - c_i + r_i) Q_i f_i(x_i)\,\mathrm{d}x$ is the expected profit of the retailer i.

By implementing the same manipulations with the single retailer problem, we obtain the following problem:

Model NBM-SLP:

$$\max_{\mathbf{r}} \quad z(\mathbf{r}) = \sum_{i=1}^{n} u_i\left(F_i^{-1}\left(\frac{p_i - c_i + r_i}{p_i - s_i}\right)\right) \tag{3.23}$$

$$\text{s.t.} \quad g(\mathbf{r}) = \sum_{i=1}^{n} r_i F_i^{-1}\left(\frac{p_i - c_i + r_i}{p_i - s_i}\right) - B \leq 0 \tag{3.24}$$

$$h_i(r_i) = -p_i + c_i - r_i \leq 0 \;\; i = 1, \cdots, n \tag{3.25}$$

$$t_i(r_i) = -c_i + s_i + r_i \leq 0 \;\; i = 1, \cdots, n \tag{3.26}$$

KKT conditions imply that an optimal solution $(r_1^*, \cdots, r_n^*)$ should satisfy constraints (3.24)-(3.26), and there must be multipliers θ, λ_i, and γ_i, $i = 1, \cdots, n$ corresponding to constraints (3.24)-(3.26), which satisfy the following equations:

$$\frac{\partial z(\mathbf{r})}{\partial r_i} = \theta \frac{\partial g(\mathbf{r})}{\partial r_i} + \lambda_i \frac{\partial h_i(r_i)}{\partial r_i} + \gamma_i \frac{\partial t_i(r_i)}{\partial r_i}, i = 1, \cdots, n \tag{3.27}$$

$$\theta \left[B - \sum_{i=1}^{n} r_i F_i^{-1} \left(\frac{p_i - c_i + r_i}{p_i - s_i} \right) \right] = 0 \tag{3.28}$$

$$\lambda_i [p_i - c_i + r_i] = 0, \;\; i = 1, \cdots, n \tag{3.29}$$

$$\gamma_i [c_i - s_i - r_i] = 0, \;\; i = 1, \cdots, n \tag{3.30}$$

$$\theta \geq 0, \;\; \lambda_i, \gamma_i \geq 0, i = 1, \cdots, n \tag{3.31}$$

Remark 3.1 *The problem is well-posed, i.e. for any r_i, the optimal solution of the lower level problems, $Q_i(r_i)$ are unique for all $i = 1, \cdots, n$*

Proposition 3.2 *If $0 \leq B \leq \sum_{i=1}^{n} (c_i - s_i) D_{max}^i$, the budget constraint will be always active.*

Proof is presented in Appendix A.1.

Proposition 3.3 *If all retailers are identical, there exists an optimal solution $(\mathbf{r}^*, \mathbf{Q}^*)$ such that all r_i and Q_i values are equal, i.e., $r_1^* = r_2^* = \cdots = r_n^*$ and $Q_1^* = Q_2^* = \cdots = Q_n^*$.*

Proof is presented in Appendix A.1.

Corollary 3.1 *When all retailers are identical, at the optimal solution $r_1^* = r_2^* = \cdots = r_n^* = r^*$ and $Q_1^* = Q_2^* = \cdots = Q_n^* = Q^*$. Thus, $r^* Q^* = B/n$ when $0 \leq B \leq \sum_{i=1}^{n} (c_i - s_i) D_{max}^i$.*

Proof is presented in Appendix A.1.

Corollary 3.1 implies that as the number of retailers increases both r^* and Q^* decrease for a given budget.

Proposition 3.4 *Assume that all cost parameters and demand distribution functions of retailers are identical and assume that without loss of generality the retailers are indexed from 1 through n in ascending order of marginal utilities at the optimal solution and there are no ties. Then, at the optimal solution we will have the following structure:* $Q_1^* < Q_2^* < \cdots < Q_n^*$ *and* $r_1^* < r_2^* < \cdots < r_n^*$.

Proof is presented in Appendix A.1.

The rebates may not be necessarily the same if utility of goods are not the same. For instance, one good is sold with an additional service whereas the other is not. One good example is that a pharmacy offering influenza vaccines and free vaccination service will have a higher utility compared to the one only selling vaccines.

3.3 Two-Echelon Problem

In this section, we investigate our problem under the classical two-echelon problem setting, which consists of a retailer and a manufacturer. The assumptions of the retailer is the same with the ones in our basic model. In addition, the manufacturer incurs a manufacturing cost of m. Note that there is no need for $c > m$ or $p > c$. In the two-echelon case, the central authority can give incentive to both parties, which are denoted by r_m for the manufacturer and r_r for the retailer, respectively. The central authority may help manufacturer to charge lower prices to the retailer by administering subsidies to the manufacturer or it may decrease the prices implicitly by assigning subsidies to the retailer. In this section, we analyze the centralized problem and manufacturer driven problem.

3.3.1 Centralized Problem

We first consider the case in which the manufacturer and retailer are owned or controlled by the same company. In this case, the company wants to maximize the expected system profit and the central authority wants to maximize the utility obtained from the company under the budget constraint. Here, we define r_t as the total subsidy amount issued to manufacturer and retailer per unit order quantity (i.e. $r_t = r_m + r_r$). Note that there is no need to optimize c in this setting. The problem under consideration can be formulated as follows:

$$\textit{Model C-BLP:} \qquad \max_{r_t} \quad u(Q) \tag{3.32}$$

$$\text{s.t.} \quad r_t Q \leq B \tag{3.33}$$

$$\max_Q \mathbb{E}[P_T(Q)] \tag{3.34}$$

$$\text{s.t. } Q \geq 0 \tag{3.35}$$

where $\mathbb{E}[P_T(Q)] = \int_0^Q (px + s(Q-x) - mQ + r_t Q) f(x)\,\mathrm{d}x + \int_Q^\infty (p - m + r_t) Q f_{B_d}(x)\,\mathrm{d}x$ is the expected profit of the system.

By following the same iterations with the previous problems, we have the following problem:

$$\textit{Model C-SLP:} \qquad \max_{r_t} \quad u\left(F^{-1}\left(\frac{p-m+r_t}{p-s}\right)\right) \tag{3.36}$$

$$\text{s.t.} \quad r_t F^{-1}\left(\frac{p-m+r_t}{p-s}\right) \leq B \tag{3.37}$$

$$r_t \geq m - p \tag{3.38}$$

$$r_t \leq m - s \tag{3.39}$$

Property 3.1 *Centralized problem turns out to be identical with single echelon system's problem. Note that the amount of subsidies, r_m and r_r, only affect the profit sharing between the retailer and the manufacturer.*

3.3.2 Manufacturer Driven Problem

In this section, we consider a hierarchical situation in which the manufacturer sets the purchasing price of the retailer c; then the retailer chooses the order quantity Q. As in the previous cases, central authority is the leader and controls the system by giving subsidies to the both parties. He administers subsidy amounts of r_m per unit sold to the manufacturer and r_r per unit ordered to the retailer. By this way, the central authority will either decrease the price of the good ordered by the retailer through subsidizing him, or influence the manufacturer to set a lower price via subsidizing the manufacturer, or both.

The multi-level formulation of the system under consideration is as follows:

Model MD-MLP:

$$\max_{r_m, r_r} \quad u(Q) \tag{3.40}$$

$$\text{s.t.} \quad (r_m + r_r)Q \leq B \tag{3.41}$$

$$r_m \geq 0 \tag{3.42}$$

$$\max\nolimits_c \ \mathbb{E}[P_m(c)] \tag{3.43}$$

$$\max\nolimits_Q \ \mathbb{E}[P_r(Q)] \tag{3.44}$$

$$\text{s.t. } Q \geq 0 \tag{3.45}$$

where,

$$\mathbb{E}[P_m(c)] = (c - m + r_m)Q \quad \text{and} \tag{3.46}$$

$$\mathbb{E}[P_r(Q)] = \int_0^Q (px + s(Q-x) - cQ + r_r Q) f(x)\,\mathrm{d}x + \int_Q^\infty (p - c + r_r) Q f_{B_d}(x)\,\mathrm{d}x \tag{3.47}$$

are the expected profits of the manufacturer and retailer, respectively.

After replacing the retailer's problem by its first order condition and Q by $Q = F^{-1}\left(\frac{p-c+r_r}{p-s}\right)$, the model can be reformulated as follows:

Model MD-BLP:

$$\max_{r_m, r_r} \quad u\left(F^{-1}\left(\frac{p-c+r_r}{p-s}\right)\right) \tag{3.48}$$

$$\text{s.t.} \quad (r_m + r_r)F^{-1}\left(\frac{p-c+r_r}{p-s}\right) \leq B \tag{3.49}$$

$$\max\nolimits_c \ \mathbb{E}[P_m(c)] = (c - m + r_m)F^{-1}\left(\frac{p-c+r_r}{p-s}\right) \tag{3.50}$$

$$\text{s.t. } -p + c - r_r \leq 0 \tag{3.51}$$

$$-c + s + r_r \leq 0 \tag{3.52}$$

$$-c + m - r_m \leq 0 \tag{3.53}$$

The constraints (3.51)-(3.52) are added to guarantee that the ratio $\left(\frac{p-c+r_r}{p-s}\right)$ takes values between 0 and 1. Also, constraint (3.53) is added to make sure that the manufacturer stays in the business.

Lemma 3.2 *If demand follows uniform distribution on $[a,b]$, the lower level problem given by (3.50)-(3.53) can be replaced by its KKT conditions.*

Proof is presented in Appendix A.1.

Note that to represent *Model-BLP* as a single level programming problem, one has to guarantee that problem stated in (3.50)-(3.53) has a unique solution. Lemma 3.2 shows that this is true if demand follows uniform distribution. However, one can show that this is not true for exponential distribution as the problem is neither concave nor convex in that case. Hence, it does not always guarantee a unique solution. Of course, one can find other distributions for which the problem given by (3.50)-(3.53) will be concave, but we will not make further analysis of it here.

Using Lemma 3.2, we create an alternative respresentation of *Model MD-BLP* for the case when demand is uniformly distributed. Let λ_i for $i = 1, \cdots, 3$ denote the KKT multipliers of constraints (3.51) through (3.53), respectively. Then, the formulation is as follows:

Model MD-SLP:

$$\max_{r_m, r_r, c, \lambda_1, \lambda_2, \lambda_3} \quad u\left(F^{-1}\left(\frac{p-c+r_r}{p-s}\right)\right) \tag{3.54}$$

$$\text{s.t.} \quad (r_m + r_r)F^{-1}\left(\frac{p-c+r_r}{p-s}\right) \leq B \tag{3.55}$$

$$\frac{\partial \mathbb{E}[P_m(c)]}{\partial c} = \lambda_1 - \lambda_2 - \lambda_3 \tag{3.56}$$

$$-p + c - r_r \leq 0 \tag{3.57}$$

$$-c + s + r_r \leq 0 \tag{3.58}$$

$$-c + m - r_m \leq 0 \tag{3.59}$$

$$\lambda_1(p - c + r_r) = 0 \tag{3.60}$$

$$\lambda_2(c - s - r_r) = 0 \tag{3.61}$$

$$\lambda_3(c - m + r_m) = 0 \tag{3.62}$$

$$\lambda_1, \lambda_2, \lambda_3 \geq 0 \tag{3.63}$$

3.3.3 Observations Obtained from Numerical Examples

In this subsection, we present a summary of results and insights obtained from numerical studies. We choose objective function as expected sales as one would be interested in increasing the adoption level of public-interest goods. We conduct our numerical studies for uniformly distributed demand. The aims of the numerical study are (i) to find out how centralized and manufacturer driven systems work and (ii) to investigate performance of manufacturer driven system compared to centralized system. The details about the numerical studies can be found in Appendix A.2. The summary of observations is as follows:

- Observation 1: *Model MD-SLP* yields infinitely many solutions for (c, r_r, r_m) when constraints (3.57)-(3.59) are not binding.
- Observation 2: As expected, expected sales and Q increase with the increase in the available budget.
- Observation 3: Results found in Tables A.1-A.5 show that centralized problem yields remarkably better solutions compared to manufacturer-driven system in terms of expected sales.

Note that application of a contract that coordinates retailer's and manufacturer's actions will lead to centralized system's solution [17].

3.4 A General Approach for a Single Echelon Model with Incentive-sensitive Demand

As the real-world cases would suggest, rebates and subsidies are frequently used to lower high costs of public-interest goods and make the goods viable to buy. Some significant examples are implementation of Clean Vehicle Rebate Project to promote electric vehicles in California[1], offering tax credits and rebates to encourage wider usage of renewable resources in US[2], and subsidizing influenza vaccine costs of children in Hong Kong [3]. While these tools are deployed to address the market adoption issues, real life statistics show that they fail to achieve socially desirable levels of usage. For instance, in 2011 Obama set a goal of having 1 million electric vehicle on the road in US by 2015, however there are only about 330,000 vehicles in 2015[4]. This type of statistics indicate that right policy requires application of multiple intervention tools simultaneously so that the intervention will have differentiated effects on system dynamics eventually accelerating the diffusion of goods. Aligned with this aim, we consider a joint intervention mechanism consisting of investment in demand-increasing strategies that will foster the demand and investment in strategies that will improve the system operation (such as subsidies, rebates or research and development investment to improve yield).

The formulations studied in the previous sections of this thesis lack the following (although they follow most of the literature):

- A subsidy rewarding the manufacturer/retailer per unit manufactured/ordered may not be always desired, as it may lead to excessive leftovers. The gap between the centralized model and decentralized model in Section 3.3 is a good indication of this observation. Additionally, following the exact number manufactured/ordered may be difficult.
- One technical issue results in giving a subsidy as done in the previous sections is its constant effect on the selling price. This is how one can utilize the same demand distribution. However, in the case of a joint intervention mechanism, we want to make sure that customers' willingness to buy price does not change even if the actual selling price differs. We achieve this with the formulation we present in this section.

[1]https://cleanvehiclerebate.org/eng
[2]http://energy.gov/savings
[3]http://www.chp.gov.hk/en/view_content/17984.html
[4]http://www.nytimes.com/2015/12/01/science/electric-car-auto-dealers.html?smid=nytcore-ipad-share&smprod=nytcore-ipad&_r=0

- Finally, budget decision is not a fixed one when we consider a model that spans over a long-time period. To work with expectations being limited by a budget level is reasonable.

Below we introduce a generic formulation of joint intervention design problem for a single echelon system. Note that the formulation can be particularized for any environment and alternative intervention mechanisms. The following notation and assumptions are used to describe the model.
p: unit revenue
c: unit acquisition cost
s: unit salvage price for unsold goods
B: budget of central authority
B_d: investment amount for demand-increasing strategies
B_r: investment amount for improving system operation (subsidies/rebates or research and development)
r: subsidy/rebate amount
Q: order or production quantity
$u()$: utility function (a general increasing concave function with respect to Q)

The general bilevel programming formulation of the problem is as follows:

$$\begin{aligned}
\textit{BLP:} \quad & \max_{B_d, B_r, r} && u(Q, B_d) && (3.64)\\
& \text{s.t.} && B_d + B_r \leq B && (3.65)\\
& && h(r, Q) \leq B_r && (3.66)\\
& && B_d, B_r \geq 0 && (3.67)\\
& && \textit{Lower Level Problem}_Q && (3.68)
\end{aligned}$$

Similar to the models in this chapter, the central authority is assigned to the role of leader with the objective of maximizing utility (3.64). Note that utility is a function of Q and B_d. The reason behind this is that the main goal is to increase adoption level in this type of environments. Adoption level is closely related with the availability of the good (Q) and demand level which is affected by investment made in demand-increasing strategies (B_d). The central authority begins by deciding on the investments made in demand-increasing strategies and strategies improving system operation, and rebate/subsidy amount. It is assumed that the investment made in demand-increasing strategies affects the demand distribution. On the other hand, investment in strategies for improving system operation will influence the operation of the follower. Given intervention scheme, the lower level decision maker devises his plan. Constraint (3.65) restricts the investments made in demand-increasing strategies and strategies improving system operation to the central authority's budget. The relation between the subsidy/rebate amount and total budget allocated to subsidies/rebates is reflected by constraint (3.66). Of course, if subsidy/rebate is omitted from the model, constraint (3.66) will be excluded. Next, we discuss alternative modeling approaches of the above formulation.

Budget: The model *BLP* decides on the allocation of a given budget among two intervention tools. It is motivated by the fact that central authority operates under a limited resource in practice. Another possibility is to decide on the budget as well. In Chapter 4, the model is extended to the case where central authority decides on the budget amount and its allocation between intervention alternatives.

Subsidy or rebate: Two common intervention tools used to improve system operation are subsidy given per unit ordered and rebate issued per unit sales. In this chapter, we analyze intervention strategies incorporating subsidies. However, we observe that this tool imposes an upper limit on the amount of subsidy to be administered which makes problem more complicated. Also, policies in practice that we will analyze through case studies offer rebates to consumers. Thus, we consider rebates in the remainder of the thesis.

For the rebate case, we assume that there is a price customer is willing to pay for the good p, and rebate r is offered to the customers by the central authority. Thus, retailer earns a revenue of $r+p$. Rebate directly changes the fractile value and so availability of the good. Note that customer base is constant with respect to changes in the rebate amount. Budget limitation over total rebate expenditures is expressed in terms of expected rebate amount registered. Hence, it may be necessary to calculate risk associated with this constraint such as expected excess budget required and maximum excess budget required.

Lower level problem: Lower level problem can be modeled depending upon the environment considered. Particularly, the follower can be a retailer, manufacturer or a coordinated manufacturer-retailer system. The key point is that the lower level problem's objective function should be concave and constraint set should be linear or convex so that it can be replaced with its KKT conditions (first order condition if it is unconstrained) to create a single level formulation.

The corresponding single level representation of *BLP* is

$$
\begin{aligned}
\textit{SLP:} \quad & \max_{B_d, B_r, r, Q} \quad && u(Q, B_d) && (3.69)\\
& \text{s.t.} && B_d + B_r \leq B && (3.70)\\
& && h(r, Q) \leq B_r && (3.71)\\
& && B_d, B_r \geq 0 && (3.72)\\
& && Q = n(B_d, r) && (3.73)\\
& && LL \leq r \leq UL && (3.74)
\end{aligned}
$$

where constraint (3.73) represents the first order condition of the lower level problem and LL and UL are the lower limits and upper limits on r, which are derived from characteristics of the lower level problem.

In the following chapters of the thesis, we provide detailed analysis of specific joint intervention mechanisms.

Chapter 4

Joint Mechanism Composed of Demand-increasing Strategies and Rebates

This chapter is partly based on [47].

4.1 Introduction

In Chapter 3, we have considered intervention through subsidies. In particular, the central authority administers subsidy per unit ordered or manufactured. However, real life cases indicate that intervention through only subsidies or rebates is not sufficient to achieve socially desirable levels of adoption for public-interest goods. Thus, in this chapter we propose two intervention tools applied simultaneously: (1) investing in demand-increasing strategies, which affects the level of the stochastic demand in the market; and (2) rebates that affect revenue per unit received by the retailer.

We consider a general setting composed of a retailer and a central authority that regulates the system through an intervention scheme. As in Chapter 3, the main goal of intervention is to maximize expected utility or social welfare rather than to solely maximize expected profit. A key issue in designing a joint intervention mechanism is to choose the intervention tools to apply. One alternative is to invest in demand-increasing strategies, such as advertising, education, research and development, and awareness campaigns, so that the demand pool is enhanced in the medium to long run. Another alternative can be either offering rebates to customers or administering subsidies to each unit sold. In fact, rebates and subsidies per unit sold operate similar to each other in terms of improving availability of the product at the retailer via increased unit revenue, and at the same time making the good more attractive for the customers given the level of their willingness to pay. So, we refer to the second tool as rebates in the rest of the chapter. Our work is the first to consider alternative strategies for intervention, affecting both supply and demand. Specifically, we propose a joint mechanism, where the central authority uses investment in demand-increasing strategies and rebates simultaneously. In some sense, then, the problem is to decide on the optimal allocation of the central authority's budget among these two intervention tools.

We formulate this setting by bilevel programming. In this case, the central authority is the leader, whose objective is to maximize social welfare, whereas the retailer is the follower, whose objective is to maximize expected profit. The central authority decides on the direct investment amount for the demand-increasing strategies and on the rebate amount per unit, then the retailer decides on the order quantity. There are few well-documented cases of direct investment response functions, but they are generally assumed to be concave for advertising (e.g. [48, 49, 50, 51]), and we follow the same assumption in our analysis. The concave response function indicates that as the money invested increases, so does the expected demand, but with a monotonically diminishing rate. On the other hand, the retailer's problem is a newsvendor problem incorporating the rebate amount. The retailer decides on the profit maximizing order quantity.

We first consider a general case for which the central authority decides on the budget amount and details of the intervention scheme. An alternative case is the one for which budget is exogenously determined but allocation of budget among intervention tools is of interest. In this chapter, we analyze both settings, but explore the former one in the numerical studies. In addition to developing the modeling perspective, we characterize the optimal intervention strategy and provide useful insights for regulating these goods. We also present three benchmark approaches for both cases: one is a no-intervention case and two are decentralized approaches that work with a predetermined rebate amount. Finally, we provide a detailed case study for the California electric vehicle market to analyze the benefit of using the proposed approach, implementing a novel parameter calibration approach.

4.2 Model I: Optimal Budget and Allocation Among Intervention Tools

We study the problem in a setting composed of a retailer and a central authority. In this context, the retailer refers to either an entity that both manufactures and sells the good, or a coordinated manufacturer-retailer system. The retailer sells the good to individual customers and by its consumption not only the buying individual but also other individuals benefit. The main goal of the central authority is to regulate the system to increase the good's availability and consumption, and hence collective societal welfare.

The central authority regulates the system by two different tools: (1) investment in demand-increasing strategies; and (2) rebates. The central authority decides on the direct investment amount made in demand-increasing strategies B_d, the total amount assigned to rebates B_r, the rebate amount r, and the budget B. Depending on B_d, the distribution function of demand changes. Note that r is a rebate available to the end customers. More specifically, let p denote the price the customer is willing to pay for the good; then the retailer earns a revenue of $p+r$ from each unit sold. This scheme helps customers buy a good that costs more money than they would otherwise be willing to pay and improves the availability of the good at the retailer. Note that in this case customer base does not change with the rebate amount, however actual price of the good differs. We define objective function as $u(Q,B_d)-B$ to maximize utility (or can be named as social welfare), $u(Q,B_d)$ reflecting benefits to society in monetary units, and B capturing the budgetary expenses of intervention mechanism.

We model the retailer's problem similar to a newsvendor problem. The retailer decides on the order quantity Q by incurring a unit acquisition cost c, gaining a unit retail price $p+r$, and a unit salvage price s for unsold goods, with the intention of maximizing the expected profit. However, the distribution of demand depends on the amount the central authority invested in demand-increasing strategies, B_d, with pdf $f_{B_d}(.)$ and cdf $F_{B_d}(.)$. Throughout the study it is assumed that the cdf of demand is monotone increasing in its argument. The monotonicity of $F_{B_d}(.)$ allows us to use the following implicit fact while showing our results: as the fractile increases, Q also increases. We assume that there is a family of demand distribution functions dependent on B_d, and that changes in the value of B_d lead to a first order stochastic dominance order between cdfs, i.e. let $\overline{B_d} > \widehat{B_d}$; then $F_{\overline{B_d}}$ has a first order stochastic dominance over $F_{\widehat{B_d}}$. Specifically, we impose the assumption that the cdf of demand at a given value is a decreasing function of B_d. Thus, it is guaranteed that as B_d increases, so does Q.

The bilevel programming formulation of the problem is as follows:

Model JM1:

$$\max_{r,B_d,B_r,B} \quad u(Q,B_d)-B \tag{4.1}$$

$$\text{s.t.} \quad B_d+B_r \leq B \tag{4.2}$$

$$r\mathbb{E}[min\{Q,D\}\,|B_d] \leq B_r \tag{4.3}$$

$$r \geq c-p \tag{4.4}$$

$$r \geq 0 \tag{4.5}$$

$$B_d, B_r \geq 0 \tag{4.6}$$

$$\max_{Q} \mathbb{E}[P(Q)|B_d] \tag{4.7}$$

where $\mathbb{E}[P(Q)|B_d] = \int_0^Q ((p+r)x + s(Q-x) - cQ) f_{B_d}(x)\,\mathrm{d}x + \int_Q^\infty (p+r-c)Q f_{B_d}(x)\,\mathrm{d}x$ is the retailer's expected profit.

Notice that D denotes the demand. (4.1)-(4.6) express the upper-level problem while (4.7) corresponds to the lower-level problem. Constraint (4.2) ensures that the money invested in B_d and B_r is not more than the budget, whereas constraint (4.3) limits the expected total rebate amount to the budget allocated to rebates. For constraint (4.3), the actual cost of rebates could be higher than B_r once the demand is realized. We will make further analysis related with this constraint in a later section. Note that B_d

determines the level of demand to be considered. Constraint (4.4) restricts the values that r can take, i.e. it assures that r is greater than $c-p$ so that the cost of underage is greater than 0. This constraint assures a minimum rebate needed to have the product available in the market. The non-negativity of r, B_d, and B_r are guaranteed by (4.5) and (4.6). Lastly, (4.7) reflects the retailer's problem.

The context discussed can be viewed as a classical leader-follower game, in which the central authority has the role of leader (or a higher-level decision maker), with the objective of maximizing utility (4.1) and the retailer has the role of follower (or a lower-level decision maker), with the objective of maximizing expected profit (4.7). Note that we do not solely maximize utility or expected profit; rather we maximize the retailer's expected profit under the dominant objective of the central authority.

Remark 4.1
(i) The total budget will be summation of B_d and B_r at the optimal solution. Thus, B can be eliminated from the formulation using equality.
(ii) $r\mathbb{E}[min\{Q,D\}\,|B_d] = B_r$ holds at the optimal solution.

Remark 4.2 *For a given B_d, B_r, and r, $\mathbb{E}[P(Q)]$ is concave in Q, thus the solution for the lower-level optimization problem is unique, implying that the rational reaction set $R(B_d, B_r, r)$ is single valued and unique. The uniqueness of $R(B_d, B_r, r)$ guarantees that the leader achieves his maximum objective (by Proposition 8.1.1, pg. 303 [5]).*

Lemma 4.1 $\mathbb{E}[P(Q)]$ *is concave in Q for every B_d, B_r, and r. This assures that the solution to the lower-level problem is unique, implying that it can be replaced by its first-order condition (by pg. 308 of [5]).*

Accordingly, *Model JM1* can be written as the following single-level mathematical program:

Model JM1-SLP:

$$\max_{r,B_d,B_r,Q} \quad u(Q,B_d)-(B_d+B_r) \tag{4.8}$$

$$\text{s.t.} \quad r\mathbb{E}[min\{Q,D\}\,|B_d]=B_r \tag{4.9}$$

$$r \geq c-p \tag{4.10}$$

$$r \geq 0 \tag{4.11}$$

$$B_d,B_r \geq 0 \tag{4.12}$$

$$F_{B_d}(Q)=\frac{p+r-c}{p+r-s} \tag{4.13}$$

A general bilevel programming problem is the most challenging of bilevel programs both theoretically and computationally. By reducing the *Model JM1* to a single-level program, we obtain a relatively easy to solve program. Henceforth, we continue our analysis with *Model JM1-SLP*, which is a standard nonlinear program with a nonlinear objective function and constraints. Note that the constraint set of *Model JM1-SLP* is not necessarily convex.

4.2.1 Special Case: Societal benefit is a linear function of expected sales

In this subsection, we analyze *Model JM1-SLP* for a specific objective function of the central authority and mean demand function.

Assumption 1 Suppose that utility function is defined as $\beta\mathbb{E}[min\{Q,D\}\,|B_d]-(B_d+B_r)$. Note that β times expected sales is used to capture the monetary benefits to society, where β is the monetary value ($) per expected sales. In practice, the central authority is generally interested in increasing the number of adopters, so expected sales is a reasonable measure to quantify benefits.

Assumption 2 Similar to the approach in the advertising literature [48, 49, 50, 51], we consider an increasing and concave response function of B_d, which is in the following form:

$$\mu(B_d) = \mu_\infty - \frac{d}{(1+kB_d)^a}, \text{ where } a,d,k > 0. \tag{4.14}$$

Specifically, mean demand increases as B_d increases, but with a monotonically diminishing rate. In this form, as B_d approaches infinity, demand distribution approaches a limiting distribution with a mean of μ_∞. Note that if other parameters of a distribution are also affected by B_d, they can be modeled similar to (4.14).

Under this utility function, we can modify the model *Model JM1-SLP* as follows:

Model SC:

$$\max_{r,B_d,Q} \quad (\beta - r)\mathbb{E}[min\{Q,D\}\,|B_d] - B_d \tag{4.15}$$

$$\text{s.t.} \quad F_{B_d}(Q) = \frac{p+r-c}{p+r-s} \tag{4.16}$$

$$r \geq c - p \tag{4.17}$$

$$r \geq 0 \tag{4.18}$$

$$B_d \geq 0 \tag{4.19}$$

We further analyze *Model SC* under specific distributions for demand. We consider exponential and lognormal distributions to represent family of distributions induced by B_d.

Proposition 4.1 *Consider the Model SC given in (4.15)-(4.19). Demand follows a family of distributions dependent on B_d, where mean of the distribution follows (4.14). If the family of demand distributions is exponential or lognormal with constant coefficient of variation, then the optimal rebate amount is independent of optimal B_d.*

Proof is presented in Appendix B.1.

Proposition 4.1 indicates that the optimal rebate amount is not affected by the investment made in demand-increasing strategies, efficiency of the strategies, and mean demand before and after investment. From another perspective, the rebates are independent of the planning horizon considered, as one would think that planning horizon considered will change the parameters of demand. From the perspective of retailer, optimal fractile value is constant, regardless of the demand parameters, as dictated by the form of the objective function.

Note that for the lognormal distribution, we hold the coefficient of variation constant with respect to the changes in the values of B_d, i.e. variation of demand increases with the increase in mean demand. Next, we consider an environment in which demand-increasing strategies will also reduce variability in the following form:

$$cv(B_d) = cv_{min} + \frac{cv_{imp}}{(1+kB_d)^a}, \quad \text{where} \quad a,k > 0. \tag{4.20}$$

Note that we can define cv_{imp} as portion of the coefficient of variation value that can be eliminated. In particular, coefficient of variation decreases as B_d increases, but with a monotonically diminishing rate. As B_d approaches infinity, the demand distribution approaches a limiting distribution with a mean of μ_∞ and coefficient of variation of cv_{min}.

Proposition 4.2 *Consider the model Model SC given in (4.15)-(4.19), mean demand function given in (4.14), and coefficient of variation function given in (4.20). If demand is lognormally distributed, then the optimal rebate amount will be dependent on the optimal B_d.*

Proof is presented in Appendix B.1.

Intuitively, if demand-increasing strategies also decrease the variability of demand, the optimal rebate amount, i.e. optimal fractile, becomes a function of B_d, as well.

4.3 Model II: Optimal Allocation of a Given Budget Among Intervention Tools

In this section, we consider a similar setting as in the previous section, however budget is exogenously determined in this case. The problem is modeled by bilevel programming and then reduced to a single level programming formulation using the uniqueness of newsvendor problem at the lower level with a similar reasoning as in *JM1*. In particular, the formulation of the problem is as the following:

Model JM2-SLP

$$\max_{r,B_d,B_r,Q} \quad g(Q,B_d) \tag{4.21}$$

$$\text{s.t.} \quad B_d + B_r \leq B \tag{4.22}$$

$$r\mathbb{E}[min\{Q,D\}\,|B_d] \leq B_r \tag{4.23}$$

$$r \geq c - p \tag{4.24}$$

$$r \geq 0 \tag{4.25}$$

$$B_d, B_r \geq 0 \tag{4.26}$$

$$F_{B_d}(Q) = \frac{p+r-c}{p+r-s} \tag{4.27}$$

Model JM2-SLP decides on B_d, B_r, r, and Q with the objective of maximizing utility (denoted by $g(Q,B_d)$) for a given budget level. The constraints are similar to those in *Model JM1*. Note that the utility function may also be affected by other variables of the system, implicitly or explicitly.

Proposition 4.3 *For an increasing concave utility function with respect to Q, the following relationships hold at the optimal solution, (r^*,Q^*,B_d^*,B_r^*):*
a) $r^*\mathbb{E}[min\{Q^*,D\}\,|B_d] = B_r^*$,
b) $B_d^* + B_r^* = B$.

Proof is presented in Appendix B.1.

By exploiting the assumptions of the demand distribution function, we have shown that the central authority always allocates all of the available budget among the two intervention tools for the benefit of the whole system and always uses all of the budget assigned to rebates. When utility is an increasing concave function with respect to Q, it exhibits diminishing marginal increases in utility as Q increases. Therefore, a higher Q is always more desirable. Note that increases in both B_d and B_r lead to an increase in Q, i.e. by affecting the distribution function and the fractile respectively.

The *Model JM2-SLP* is not necessarily convex even for a problem with a concave utility function and specific demand distribution. Thus, we limit our analysis with an increasing concave utility function with respect to Q so that one can solve the problem using the tightness of the budget-related constraints, (4.22) and (4.23).

4.4 Benchmark Models

This section explores three benchmark cases that can be used to assess the performance of our approaches given in Sections 4.2 and 4.3. The benchmark approaches considered are representations of the mechanism taking place in practice, where the rebate amount is decided by the central authority [52].

The first benchmark is an obvious one, no-intervention case, which may help us better understand the impact of intervention in this type of system. However, if $c > p$, the system would not operate without intervention. Hence, we cannot employ a no intervention scenario even as a benchmark for $c > p$ cases. Note that this benchmark applies to both optimal budget and exogenous budget models.

The second benchmark is a decentralized approach as decisions on intervention tools are not taken simultaneously and the third benchmark emerges as an extension of it. The explanations of these two benchmarks together with the formulations are presented below for each model separately.

4.4.1 Benchmark Approaches for Optimal Budget Model

4.4.1.1 Joint Mechanism with Fixed Rebate

The difference of this benchmark from the joint mechanism is that the problem is solved for a prespecified rebate amount. In other words, decisions about intervention tools are not made jointly; specifically, the rebate amount is preset by the central authority. Under certain demand functions considered in Proposition 4.1, the preset amount by the central authority may be the optimal solution. However, under conditions stated by Proposition 4.2, the rebate amount is a function of B_d.

Our model formulation for this approach is as follows:

$$\textit{Model JMFR1:} \qquad \max_{B_d, B_r, Q} \quad u(Q,B_d) - (B_d + B_r)$$
$$(4.9), (4.12), (4.13)$$

4.4.1.2 Fixed Rebate Approach

Inspired from the previous case, we construct another reference, in which the central authority regulates the system only by rebates that are predetermined by the central authority (i.e. B_d=0 in this case). The aim of this approach is to see how the system operates with a preconcerted rebate amount. No optimization is needed; newsvendor quantity and expected sales corresponding to the predetermined rebate amount are computed, and central authority will assign B_r accordingly. The following lines summarize *Model FRA1*.

$$\textit{Model FRA1:} \qquad \text{Compute} \quad u(Q,B_d=0) - B_r$$
$$\text{where} \quad F_{(B_d=0)}(Q) = \frac{p+r-c}{p+r-s}$$
$$r\mathbb{E}[min\{Q,D\}\,|B_d=0] = B_r$$

4.4.2 Benchmark Approaches for Exogenous Budget Model

4.4.2.1 Joint Mechanism with Fixed Rebate

As in the joint mechanism with fixed rebate for optimal budget model, the problem is solved for a predetermined rebate amount. In this case; since r is fixed, the profit maximizing quantity may not be feasible to satisfy the budget-related constraints, i.e. the budget may not be enough to attain rebates for the optimal newsvendor quantity. In that case, the central authority will devote all available budget to the rebates to attain a quantity nearest to the optimal newsvendor quantity. Thus, we write the newsvendor optimality condition as an inequality constraint in the problem formulation. Note that one can also show that all of the available budget will be used for a concave utility function with respect to Q (similar to the proof of Proposition 4.3).

Our model formulation for this approach is as follows:

Model JMFR2:

$$\begin{aligned} \max \quad & g(Q,B_d) && (4.28)\\ \text{s.t.} \quad & B_d + B_r \leq B && (4.29)\\ & r\mathbb{E}[min\{Q,D\}\,|B_d] \leq B_r && (4.30)\\ & B_d, B_r \geq 0 && (4.31)\\ & F_{B_d}(Q) \leq \frac{p+r-c}{p+r-s} && (4.32) \end{aligned}$$

4.4.2.2 Fixed Rebate Approach

The formulation is very similar to the formulation given for the joint mechanism with fixed rebate and is shown below:

Model FRA2:

$$\begin{aligned} \max_{B_r,Q} \quad & g(Q,B_d=0) && (4.33)\\ \text{s.t.} \quad & 0 \leq B_r \leq B && (4.34)\\ & r\mathbb{E}[min\{Q,D\}\,|B_d=0] \leq B_r && (4.35)\\ & F_{(B_d=0)}(Q) \leq \frac{p+r-c}{p+r-s} && (4.36) \end{aligned}$$

With a similar reasoning as in the joint mechanism with fixed rebate, the newsvendor condition is represented as an inequality (see constraint (4.36)). How the constraint works in this case can be summarized as follows (for a concave utility function with respect to Q): (1) If the budget is not enough to issue rebates up to the optimal newsvendor quantity, it will bring the quantity to the point that budget allows, or (2) It may be that the budget is higher than the rebate amount assigned to the expected sales of the optimal newsvendor quantity. Then, Q will be equal to the newsvendor optimal, but not all of the available budget will be utilized.

4.5 Case Study: The California Electric Vehicle Market

In this section, we employ the joint intervention mechanism introduced in the previous section to explore the intervention mechanism in the California electric vehicle (EV) market. As it is more general, we conduct the case study with the optimal budget model and its benchmarks (i.e. *Model SC*, *Model JMFR1*, *Model FRA1*).

According to a report of the World Business Council for Sustainable Development [53], the global light duty vehicle fleet is projected to be two billion by 2050. Globally, light duty vehicles are the main contributor of greenhouse gas emissions and depletion of fossil fuel resources [54]. As a response to the increasing pattern in vehicles on the road and its associated implications on climate change and resources, EVs have received increased attention from environmentalists, industry, governments, and academics in the last decade, and have emerged as a strong alternative to conventional internal combustion engine vehicles. As EVs are considered a significant technological breakthrough with potential environmental benefits, they can be categorized as public-interest goods. However, they face a combination of cost and performance issues that limit their competitiveness, which is why their introduction in the market is ensured by governmental policies. Foremost examples of such policies are in the US and European Union, which promote EVs through several programmes and strategies. A notable number of governments have also announced the number of EVs they aim to have on roads by certain dates. For instance, in 2011, US President Obama expressed a target of one million EVs on the road by 2015.[1]

In this study, we consider the intervention design problem for a specific application, the California EV market. Note that we refer to plug-in hybrids (PHEVs) and all electric vehicles (also called battery-electric vehicles (BEVs)) as EVs throughout the case study. In the US, various subsidy schemes have been adopted at the federal level and even the local level to encourage EV sales. Under the current policy at the federal level, the government offers subsidies in the form of a federal income tax credit of up to $7,500 for EVs purchased in or after 2010, based on the capacity of the battery used to fuel the vehicle.[2] At the state level, California implements a special consumer incentive program, the Clean Vehicle Rebate Project (CVRP), to promote the adoption of clean vehicles.[3] The project was launched in March 2010 and expected to end in 2015. Under the CVRP, individuals, nonprofits, government entities, and businesses can receive a rebate up to $5000 on top of the $7500 federal tax credit for the purchase of eligible vehicles, which include zero emission vehicles (ZEVs) (BEVs are categorized as ZEVs), PHEVs, neighborhood electric vehicles (NEVs), and zero emission motorcycles (ZEMs). According to current statistics, California is the leading state in clean vehicle adoption: although the state constitutes 10% of the total US car market, 40% of all PHEVs purchases are from California.[4] Also, a May 2013 PHEV driver survey [5] reports that 47% of purchasers rate the state rebate as the most important factor in their decision to purchase a PHEV. From these statistics, we can better understand the significance of a state rebate on the motivation for EV purchases.

Most of the infrastructural investment to increase the efficiency and reliability of the technology is expected to attract more customer demand (see page 8, [55]). Following the discussion on page 6-7 of the document [55], on the other hand, these R&D investments mostly were completed before 2012, and hence we assume that those effects are already reflected in the current demand estimates

[1] http://www.whitehouse.gov/the-press-office/2011/01/25/remarks-president-state-union-address

[2] http://www.fueleconomy.gov/feg/taxevb.shtml

[3] http://energycenter.org/clean-vehicle-rebate-project

[4] http://www.government-fleet.com/channel/green-fleet/news/story/2013/03/california-ev-and-zero-emission-rebate-program-extended.aspx?prestitial=1

[5] http://energycenter.org/clean-vehicle-rebate-project/vehicle-owner-survey/may-2013-survey

Unfortunately, however, the statistics indicate that current policies are insufficient to reach nationwide goals on clean vehicle market growth. According to an Information Technology and Innovation Foundation report [54], the right policy to encourage mass adoption of electric vehicles is a combination of subsidies and battery research funding to remove technological barriers, which parallels the mechanism we introduce in the previous section. Electric vehicles have been only recently introduced in the market and their ongoing development is open ended, dependent on investments in battery improvement technologies and production processes. Several research projects are currently underway to improve battery technology, but these developments must be fostered more aggressively. Thus, balancing available funds between research and development, and rebates is a key issue in resolving the adoption problem.

We use the newsvendor context in the EV example, which implies that there is a single period and a monopolist retailer. Obviously, the retailer does not make a single production decision; instead he is making major decisions each year, and then more detailed decisions each month or week. Hence, it is critical to emphasize that the quantities found should be interpreted as capacity decisions of the retailer. Also, there are many EV models and hence competing manufacturing firms available in the market. However, in this problem we aggregate the retailers and investigate the industry-wide problem, because our main concern is the reaction of the industry to the intervention mechanism.

Specifically, our numerical study addresses the following issues: (1) the value of the joint mechanism, (2) the performance of the joint mechanism in short-term versus long-term planning, (3) the impact of uncertainty on the results, and (4) the applicability of the proposed model.

Before proceeding with the numerical results, we first describe the demand model, objective function, and how we chose and calibrated parameter values.

4.5.1 Demand model and objective function

We use two different distributions to represent EV demand and conduct separate computational studies to evaluate the robustness of the results with respect to distribution. The demand of a product like an EV, which is in the early stages of adoption, is expected to be highly uncertain. So, at first we assume demand to be exponentially distributed. Subsequently, we consider the case that demand follows a lognormal distribution, as it allows us to assess the impact of demand uncertainty on the results. Note that we consider the mean demand function given in (4.14) for both distributions.

Motivated by the EV market's circumstances, we choose the central authority's utility function as given by *Assumption 1* in Section 4.2.1. By utilizing this objective, we choose expected sales value to assess the benefits to society for this application. The US government is concerned with increasing the number of EVs on the road, and President Obama has announced an adoption target. Therefore, the expected sales will be a realistic function to capture benefits to society and it is consistent with the current market environment.[6]

4.5.2 Choice of parameter values

The cost parameters in this numerical study are based on the market data of a specific model, the Nissan Leaf. The Leaf is an all electric vehicle constituting a global market share of 45% as of the first quarter of 2014 [56]. The manufacturer's suggested retail price (MSRP) for the Leaf 2013 is $28,800 [57] in the US, and it is eligible for a rebate of $2,500 by the CVRP [7] on top of a federal income tax credit of $7,500.[8] Thus, the price the customer is willing to pay is reduced to $18,800. Also, from market data we find out that the factory invoice, i.e. the amount the manufacturer charges the dealer

[6]One discussion is whether increasing sales of vehicles really does benefit society, regardless of whether what is sold is an EV. The utility function considered is expected to decrease for some large sales levels due to both concavity of expected sales and subtraction of budgetary expenses from monetary value of expected sales.

[7]http://energycenter.org/clean-vehicle-rebate-project

[8]http://www.fueleconomy.gov/feg/taxevb.shtml

(c), is \$26,986 [58] [9].

The demand model's parameters are derived from the California Energy Commission's report on state energy demand forecasts between the years 2012 and 2022 [59] and statistics obtained from the California Center for Sustainable Energy (CCSE)'s website.[10] The California Energy Commission's report tabulates the projected number of BEVs and PHEVs on the road for low scenario and high scenario cases for selected years between 2011 and 2022. Accordingly, the forecasts of the relevant periods are listed in Table 4.1.

Table 4.1: Demand forecasts of EVs

Period	**Low Scenario**	**High Scenario**
2011-2013	43,113	332,559
2011-2015	108,907	1,081,703
2011-2022	834,489	3,574,670

The CCSE's website offers interactive access to data and analyses of the CVRP project. From the database accessed at the end of January 2014, we determine that the rebates issued under this program as of the end of 2013 were approximately \$95 million for 45,000 vehicles (note that we only consider rebates given to ZEVs and PHEVs in this calculation). Thus, the realized rebate is \$2116 per vehicle for the current case in addition to the federal tax credit of \$7500.

We utilize the current structure of the intervention mechanism and realized outcomes to set the demand model's parameters (μ_∞ and d in equation (4.14)) for the three years period of 2011 through 2013, and set the salvage value to its final values. As noted earlier, r is \$2116 per vehicle and sales up to end of 2013 were 45,000. By setting expected sales equal to 45,000 we obtain a condition that yields a relationship between s and $\mu_\infty - d$ when solved together with the newsvendor optimality condition, particularly for each distribution. Note that these conditions are determined under the assumption that no investment is made in battery development during these years (i.e. $B_d = 0$). Note that this is consistent with what is reported on pages 6-7 of [55]. However, we can also interpret the value of B_d as additional investment, if the current policy

[9] We assume that this environment is composed of a retailer and a central authority. Thus, we consider the price charged to dealer by manufacturer for c.

[10] http://energycenter.org/clean-vehicle-rebate-project/cvrp-project-statistics

includes investment for battery development. We test our model for both low and high salvage values, which are 65% and 80% of the MSRP value, respectively. Following the conditions we derived, s and $\mu_\infty - d$ pairs considered for the current structure appear to be as tabulated in Table 4.2. Next, we find d values corresponding to these pairs by fixing μ_∞ to the total forecast of the high scenario for these years, 332,559. Notice that as the salvage value increases so does d. This result indicates that the potential to improve demand by investing in battery development is high for larger salvage values. Moreover, we assume the values of a and k to be, respectively, 1.1 and 10^{-8} throughout the analysis.

Table 4.2: Demand model's parameters for base case scenario

Distribution	cv	s	$\mu_\infty - d$	d	α
Exponential	1	23,040	169,175	163,384	0.56
	1	18,720	305,119	27,440	0.09
Lognormal	0.8	23,040	97,543	235,016	0.81
	1	23,040	118,124	214,435	0.74
	1.2	23,040	141,205	191,354	0.66
	0.8	18,720	125,453	207,106	0.72
	1	18,720	159,500	173,059	0.60
	1.2	18,720	198,963	133,596	0.46

Suppose that the low scenario occurs with probability α. Combining the estimate of $\mu_\infty - d$, and the yearly forecasts in years 2011 and 2013 for the low and high scenarios (i.e. $\alpha(43,113) + (1-\alpha)(332,559) = \mu_\infty - d$), we obtain α values, as in Table 4.2. Assuming the same state of the world is preserved, we use α values to estimate the demand parameters of future periods for each particular data set. Similar to Table 4.2 above, we present the demand model's parameters to be used for medium- and long-term scenarios in Appendix B.2.

To determine the monetary value per expected sales (β), we use *Model JM2-SLP* to calibrate the parameter. We specifically solve *Model JM2-SLP* with the objective of maximizing expected sales. As input, we rely on the cost and demand model's data described above and we consider the budget spent as of the end of 2013 ($95 million). We solve the the problem for exponential distribution and lognormal distribution with varying coefficient of variation values. Next, we extract the Lagrange multiplier value of constraint (4.22), which gives us the marginal increase in the expected sales from a unit relaxation of the budget. Note that reciprocal of the Lagrange multiplier corresponds to the monetary value of expected sales, β. We report the estimated β values for each case in Table B.3 in Appendix B.2. To be inclusive, we consider the range for β as [3200-5100], and use the upper and lower limit, and intermediate value of the range in the numerical studies, which are $\{3200, 4150, 5100\}$.

We conduct three sets of analyses for exponential distribution and lognormal distribution with varying coefficient of variation values: (1) base-case scenario (current structure) using the estimates discussed in this subsection, (2) medium-term scenario including the years 2011 through 2015, and (3) long term scenario including the years 2011 through 2022.

Before continuing with the numerical results, we list the parameters that take the same values for each scenario: $p = 26,300$, $c = 26,986$, $a = 1.1$, and $k = 10^{-8}$. Note that $p = 26,300$ considers 18,800, amount customer is willing to pay, plus 7,500 tax credit that comes from the federal government, which is not a part of California's budget. Further, if lognormal distribution is used to represent the demand, we restrict our analysis for constant coefficient of variation.

4.5.3 Main Results

The cases considered in the computational study are labeled and summarized in Table 4.3. Notice that the letters in labels are assigned in the order of increasing values of β first, then in increasing values of coefficient of variation. For each set, we tabulate the results in Appendix D for the joint mechanism (JM), and also for the joint mechanism with fixed rebate (JMFR) and fixed rebate approach (FRA), which can be regarded as benchmarks. The tables include utility values, expected sales, details of the mechanisms, mean demand, and expected profit of the retailer, which is calculated by expression (4.7). For the case study, we solve the joint mechanism with fixed rebate and fixed rebate approach with a given rebate of \$2116, which is the current realized rebate in California. A no-intervention case cannot be employed as a benchmark for this case, because $c > p$ and rebate must be given for the system to operate. It is necessary to reemphasize that the quantities presented throughout the study should not be interpreted as the number of vehicles to be manufactured, but as the capacity plan of the retailer. Finally, notice that the rebate amount is found for given the federal tax credit of $7,500 throughout the analysis, because we only focus on California's policy, rather than on any other policy.

Table 4.3: Cases considered in the computational study

Case no.	Distribution	cv	Horizon	s ($)	β ($)
1a, 1b, 1c	Exponential	1	Base Case	23,040	$\{3200, 4150, 5100\}$
2a, 2b, 2c	Exponential	1	Base Case	18,720	$\{3200, 4150, 5100\}$
3a-3i	Lognormal	$\{0.8, 1, 1.2\}$	Base Case	23,040	$\{3200, 4150, 5100\}$
4a-4i	Lognormal	$\{0.8, 1, 1.2\}$	Base Case	18,720	$\{3200, 4150, 5100\}$
5a, 5b, 5c	Exponential	1	Medium Term	23,040	$\{3200, 4150, 5100\}$
6a, 6b, 6c	Exponential	1	Medium Term	18,720	$\{3200, 4150, 5100\}$
7a-7i	Lognormal	$\{0.8, 1, 1.2\}$	Medium Term	23,040	$\{3200, 4150, 5100\}$
8a-8i	Lognormal	$\{0.8, 1, 1.2\}$	Medium Term	18,720	$\{3200, 4150, 5100\}$
9a, 9b, 9c	Exponential	1	Long Term	23,040	$\{3200, 4150, 5100\}$
10a, 10b, 10c	Exponential	1	Long Term	18,720	$\{3200, 4150, 5100\}$
11a-11i	Lognormal	$\{0.8, 1, 1.2\}$	Long Term	23,040	$\{3200, 4150, 5100\}$
12a-12i	Lognormal	$\{0.8, 1, 1.2\}$	Long Term	18,720	$\{3200, 4150, 5100\}$

4.5.3.1 Base-case scenario (2011-2013)

For this scenario set, we consider cases 1a through 4i and demonstrate their associated results in Tables B.4 through B.6 in Appendix B.3.

When exponential distribution is used to represent demand, we observe that the joint mechanism is not applied in general, mainly due to the structure of distribution and the cost values. Since $c > p$ for the vehicles and uncertainty is very high, the central authority gives priority to increasing the vehicle's profitability to encourage the retailer to order more. However, when lognormal distribution is under consideration, the joint mechanism is implemented for most of the cases.

For this scenario set, we report the percentage improvement obtained by implementing the joint mechanism compared to the current policy (*Model FRA*) for the medium β value in Table 4.4. The percentage values indicate that the percentage utility loss is minimal, less than 1%, when demand distribution is exponential. Thus, we can say that the current policy is reasonable if exponential distribution is a better candidate to represent the demand. On the other hand, the joint mechanism performs better than the current policy under lognormal distribution.

One can also see from the solutions that the changes in results are as expected in response to the changes in β. Particularly, utility, expected sales, rebate amount, quantity ordered, and the retailer's expected profit are increasing in increasing β values. Also, for the cases that implement the joint mechanism, B_d increases if β increases, which consequently makes the joint mechanism more valuable. In summary, as very much expected, the adoption of vehicles is accelerated with an increase in the benefits to society per unit of expected sales.

Table 4.4: Percentage improvement of the utility with respect to current policy when β=4150

	s=$23,040		s=$18,720	
cv	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		47.0%		19.8%
1	0.03%	20.1%	0.8%	5.4%
1.2		6.5%		3.0%

4.5.3.2 Medium- (2011-2015) and long-term scenarios (2011-2022)

The details of the solutions for the cases considered can be found in Tables B.7 through B.9 and in Tables B.10 through B.12 in Appendix B.3 for medium- and long-term, respectively.

After analyzing all scenarios, we see that the value of the joint mechanism in terms of utility is substantial for the cases with high *s* or *d* values. Moreover, we observe that the value of the joint mechanism is especially recognized in long-term planning (see Table 4.5). Long-term planning allows one to clearly see the evolution of demand by the investment amount and thus helps the central authority better manage the budget.

The other observations and findings related to mechanism performance are similar to the base-case.

Table 4.5: Percentage improvement of the utility with respect to current policy in the long-term when β=4150

	s=$23,040		s=$18,720	
cv	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		123.7%		85.0%
1	34.7%	87.5%	0.8%	49.2%
1.2		60.2%		24.8%

4.5.3.3 Consistency check with US administration targets

We perform the medium-term scenario analysis to observe whether the 2015 goals[11] are met under the mild assumption that the same state of the world is preserved. As discussed earlier, California constitutes 10% of the total car market in 2013. Thus, using 10% the goal for our case emerges as having about 100,000 EVs on the road in California by 2015. On the other hand, 2013 statistics on EV purchases reveal that 40% of sales are in California. The results obtained by joint mechanism take values between 100,000 and 400,000, which imply that the numbers obtained by the proposed mechanism are within the 10%-40% bound. This can be interpreted as follows: as the number of vehicles on the road increases, one would expect California dominance on sales percentage to drop, as there will be increasing sales in other US states as well.

Moreover, according to an article published in New York Times[12], there are 150,000 electric vehicles in California by the end of 2015. Expected sales values found by fixed rebate approach (reflecting the current practice) in the medium term are very close to the realized sales, i.e. in the range of $[134,600,146,600]$, which can be considered as another benchmark validating our parameter estimations.

4.5.4 Analysis of Results

In this section, we use the numerical results provided in the previous section as a basis to further investigate two main issues: (1) the impact of uncertainty on the solutions, and (2) expected excess budget required.

4.5.4.1 Impact of uncertainty:

The results of the lognormal distribution case indicate that demand uncertainty can have a huge impact on the results, hence this leads us to investigate the impact of

[11] http://www.whitehouse.gov/the-press-office/2011/01/25/remarks-president-state-union-address

[12] http://www.nytimes.com/2015/12/01/science/electric-car-auto-dealers.html?smid=nytcore-ipad-share&smprod=nytcore-ipad&_r=0

uncertainty on four specific outcomes: (i) rebate amounts issued, (ii) the retailer's expected profit, (iii) utility attained, and (iv) percentage improvement compared to fixed rebate approach. We report the analysis for only one salvage value, i.e. \$23,040, at the medium β level, i.e. 4150, since the findings are similar to other combinations of salvage value and β values. Tables 4.6, 4.7, 4.8, 4.9 and 4.10 show how each of these outcomes varies with the level of uncertainty under different horizons.

- *Rebate amount*

  The impact of the increase in demand variability is in two levels, i.e. it decreases the potential to improve demand (d value) while increasing the retailer's risks of over ordering and under ordering. These conditions thus result in larger rebate amounts for higher coefficient of variation values. Moreover, we observe that the rebate amounts remain constant with respect to changes in the horizon length as shown in Proposition 4.1.

Table 4.6: Rebate Amounts (\$) when $\beta = 4150$ and $s = 23,040$

cv	Base Case		Medium Term		Long Term	
	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		1,569		1,569		1,569
1	2,147	1,689	2,147	1,689	2,147	1,689
1.2		1,785		1,785		1,785

- *Retailer's expected profit*

  The values given in Table 4.7 are the retailer's expected profit for the whole horizon of the associated scenario. When comparing the expected profit for varying demand uncertainty levels, as expected profit is smaller for higher values of the coefficient of variation. This observation implies that the retailer suffers from increasing levels of demand uncertainty in terms of expected profit.

Table 4.7: Retailer's expected profit (\$($\times 10^6$)) when $\beta = 4150$ and $s = 23,040$

cv	Base Case		Medium Term		Long Term	
	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		49.6		215.7		822.7
1	36.9	42.7	171.8	192.3	674.7	743.0
1.2		36.8		170.1		663.8

- *Utility and percentage improvement with respect to the current policy*

  The best results in terms of utility (or utility per year, which can roughly be found by dividing the numbers in Table 4.8 by the number of years considered in the corresponding case) appears when the coefficient of variation is lowest. Moreover, the results in Table 4.9 display the negative impact of uncertainty on the performance of the joint mechanism relative to the current policy (fixed rebate approach). The reason behind this finding is that the investment made in battery development only affects the mean of the demand while increasing the variation proportionally. However, if a demand-increasing strategy that will also reduce variability is implemented, the joint mechanism will be more effective for higher demand values.

Table 4.8: Utility ($\$(\times 10^6)$) when $\beta = 4150$ and $s = 23,040$

cv	Base Case		Medium Term		Long Term	
	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		134.5		656.2		2,833.9
1	91.6	109.9	351.1	515.1	1,487.3	2,244.2
1.2		97.5		422.1		1,830.9

Table 4.9: Percentage improvement of utility achieved by joint mechanism with respect to fixed rebate approach (%) when $\beta = 4150$ and $s = 23,040$

cv	Base Case		Medium Term		Long Term	
	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		47.0%		139.6%		123.7%
1	0.03%	20.1%	20.9%	84.1%	34.7%	87.5%
1.2		6.5%		48.5%		60.2%

  Another benchmark to use would be joint mechanism with fixed rebate (*Model JMFR1*). *Model JMFR1* allows for spending on demand-increasing strategies, while setting the rebate value to its current level. Percentage improvement of utility achieved by *Model JMFR1* relative to current practice is presented in Table 4.10. Note that considering both intervention strategies, even if one of them is set with respect to other considerations, will improve today's solution.

Table 4.10: Percentage improvement of utility achieved by joint mechanism with fixed rebate with respect to fixed rebate approach (%) when $\beta = 4150$ and $s = 23,040$

cv	Base Case		Medium Term		Long Term	
	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		32.1%		117.8%		105.7%
1	0.0%	12.8%	20.8%	73.4%	34.7%	77.8%
1.2		2.9%		43.1%		55.0%

4.5.4.2 Expected excess budget required

We express the budget constraint on the amount of rebates (constraint (4.3)) in terms of expected sales. This formulation may lead to the discovery that the actual cost of rebates is higher than B_r once the demand is realized. Thus, we quantify the expected excess budget required to check whether the amounts are reasonable. Defining $\mathbb{E}[EB]$ as expected excess budget required, we measure it by

$$\mathbb{E}[EB] = r \times [\int_{E[sales]}^{Q} (x - E[sales]) f_{B_d}(x) dx + \int_{Q}^{\infty} (Q - E[sales]) f_{B_d}(x) dx].$$

Note that the expected budget overflow is equal to this amount.

Table 4.11 displays the expected excess budget required and its percentage relative to the applicable budget in parentheses, respectively. Again, we only show the results for the salvage value of \$23,040 at the medium β value for the three mechanisms considered. Recall that the rebates issued under the joint mechanism are less in relation to the joint mechanism with fixed rebate and fixed rebate approach, which is why in general the percentage of $\mathbb{E}[EB]$ relative to budget is larger for the joint mechanism with fixed rebate, and fixed rebate approach. The results indicate that the government has more risk if it regulates the system by a single intervention tool. Moreover, if we evaluate the expected excess budget required on the basis of the percentage of budget under consideration, we observe that the percentages vary from 3.1% to 12.4%. Thus, we can conclude that the expected excess budget required does not appear to be too large relative to government's budget.

Note that this comparison can also be made with maximum excess budget required. The expression for the worst case expected excess budget required is given by $r(Q - E[sales])$.

Table 4.11: Expected excess budget required (\$($\times 10^6$),%) when $\beta = 4150$ and $s = 23,040$

Mechanism	cv	Base Case		Medium Term		Long Term	
		Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
JM	0.8	(12.1,12.4%)	(5.3,3.1%)	(56.6,10.6%)	(23.3,3.4%)	(222.1,11.2%)	(88.7,3.9%)
	1		(5.8,4.3%)		(26.2,4.4%)		(101.2,5.0%)
	1.2		(6.0,5.7%)		(27.6,5.4%)		(107.6,6.0%)
JMFR	0.8	(11.6,12.2%)	(12.3,5.3%)	(54.1,10.4%)	(54.5,5.6%)	(212.3,11.0%)	(209.5,6.1%)
	1		(11.0,6.3%)		(50.3,6.4%)		(195.2,7.0%)
	1.2		(9.8,7.5%)		(45.5,7.1%)		(178.0,7.6%)
FRA	0.8	(11.6,12.2%)	(6.5,6.8%)	(36.9,12.2%)	(19.4,6.8%)	(140.0,12.2%)	(89.9,6.8%)
	1		(7.4,7.8%)		(22.6,7.8%)		(96.7,7.8%)
	1.2		(8.1,8.5%)		(25.2,8.5%)		(101.3,8.5%)

4.6 Extensions of Exogenous Budget Case

In the computational studies thus far, we have utilized the optimal budget model (*Model SC*) and its benchmarks to explore the performance and implications of our proposed intervention mechanism. We now consider the exogenous budget model (*Model JM2-SLP*) and investigate the following issues: (i) the performance of joint mechanism including subsidies per unit ordered instead of rebates and (ii) a possible scheme for coordination.

We use the data explained in Section 4.5.2 for cost and demand model's parameters in the numerical studies. For sensitivity analysis with respect to the budget amount, we take values that are 20% lower and higher than the current budget allocated until the end of 2013 under the CVRP project: \$95 million. Moreover, we choose the expected sales value to assess the utility.

4.6.1 Subsidy Given Per Unit Ordered

In our main analysis, we assume that rebate is issued per unit sold in order to make the goods more viable for the customers and to stimulate the retailer to order more. Another common incentive used is to introduce retailer subsidies per unit ordered so that retailer would increase his order quantity. Thus, an alternative is to intervene in the system through subsidies given per unit ordered instead of rebates in addition to demand-increasing strategies. For this case, we can reformulate the problem with a similar reasoning as follows:

Model JM3-SLP

$$\max_{r,B_d,B_r,Q} \quad g(Q,B_d) \tag{4.37}$$

$$\text{s.t.} \quad B_d + B_r \leq B \tag{4.38}$$

$$rQ \leq B_r \tag{4.39}$$

$$r \geq c - p \tag{4.40}$$

$$r \leq c - s \tag{4.41}$$

$$B_d, B_r \geq 0 \tag{4.42}$$

$$F_{B_d}(Q) = \frac{p+r-c}{p-s} \tag{4.43}$$

Tables B.14 through B.16 in Appendix B.4 present the results of *Model JM2-SLP* and *Model JM3-SLP* for the base-case scenario. As the findings are similar for medium- and long-term scenarios, we only report the results for the base-case. With *Model JM3-SLP*, we observe an improved performance relative to *Model JM2-SLP* in terms of utility, which is used as expected sales throughout the computational studies. Comparison of these models analytically is an interesting future research question.

Although retailer subsidy case shows an improved performance compared to mechanism with rebates in terms of utility attained, the applicability of subsidies should be put into perspective. Regarding retailer subsidies, it cannot be guaranteed that the retailer uses the grant only for the benefit of this good. Thus, we can claim that the efficiency of financial support given to retailer can be limited.

4.6.2 Coordination

So far we have analyzed a decentralized system, where the retailer's decision is controlled by a central authority. However, there may be the case where, the system is completely centralized, i.e. the retailer is owned by the central authority and thus decisions about the intervention mechanism and order quantity are made by a single entity simultaneously. We have a single-level model for this case, which is formulated as follows:

$$\max_{B_d,Q} \quad g(Q,B_d) \tag{4.44}$$

$$\text{s.t.} \quad B_d + cQ \leq B + p\mathbb{E}[min\{Q,D\}\,|B_d] + s\mathbb{E}[max\{Q-D,0\}\,|B_d] \tag{4.45}$$

The fundamental difference in this model is that budget includes expected revenue and salvage in addition to the central authority's available fund. It is thus straightforward to confirm that the centralized solution will always give better solutions in terms of utility compared to the original model because the former operates with a higher budget and ignores the objective of the retailer. Although it does not include a rebate as an intervention tool, one can denote and compute the implied rebate by $\hat{r} = (B - B_d)/\mathbb{E}[min\{Q,D\}\,|B_d]$, and can subsequently find the retailer's implied expected profit with the realized rebate. Another way to interpret this implied rebate is through the minimum rebate amount that can be issued under the joint mechanism. Also, one can further show that the retailer's expected profit will be zero under the centralized solution. With this in mind, we can conclude that coordination can be achieved only when the retailer's expected profit is zero or when operating with a higher budget value. Obviously, the retailer would not be willing to comply with this policy, which begs the question of whether coordination is possible. This question will be discussed in the next section. We do not present any numerical examples regarding this model because this policy is not applicable in real life.

A proposal for coordination:

Under the centralized system, the central authority plans the budget allocation among intervention tools and order quantity such that the overall utility of the system is maximized. However, the objective/expected profit of the retailer is zero, because the impact of central authority's actions on the retailer is ignored. Thus, coordination requires directly giving a lump sum amount to the retailer so that he is not affected by coordination. We can ensure this by imposing an additional constraint in the centralized model to guarantee that the retailer earns at least the same profit as in the joint mechanism. Note that coordination is possible under full information only. Let $\mathbb{E}[P(Q^{JM2-SLP})]$ denote the retailer's expected profit based on *Model JM2-SLP*. Then, the model giving a coordinated solution is as follows:

$$
\begin{aligned}
\max_{B_d, Q} \quad & g(Q, B_d) && (4.46) \\
\text{s.t.} \quad & B_d + cQ \leq B + p\mathbb{E}[min\{Q, D\}\,|B_d] + s\mathbb{E}[max\{Q-D, 0\}\,|B_d] && (4.47) \\
& \int_0^Q ((p+\hat{r})x + s(Q-x) - cQ) f_{B_d}(x)\,\mathrm{d}x + \int_Q^\infty (p+\hat{r}-c)Q f_{B_d}(x)\,\mathrm{d}x \geq \mathbb{E}[P(Q^{JM2-SLP})] && (4.48)
\end{aligned}
$$

We can also calculate the expected excess budget required for this model with a similar reasoning as in the joint mechanism. The formula used is as follows:

$$(p-s) \times \int_0^{E[sales]} (E[sales]-x) f_{B_d}(x) dx$$

When we analyze the results, we recognize that the proposal for coordination results in higher utility, rebate, order quantity, and B_r values relative to the joint mechanism, as expected. Coordination brings remarkable benefits in terms of utility, up to 8.4%, compared to the joint mechanism. It is interesting to recognize that the expected excess budget required comprised in the coordinated approach is relatively higher in comparison with the joint mechanism (*Model JM2-SLP*). Nevertheless, comparing expected excess budget values on the percentage of available budget basis gives lower percentage values for the coordinated solution relative to the joint mechanism. However, these values still highlight the increased budgetary burden of the coordinated approach on the government.

4.7 Concluding Remarks

In this chapter, we study the problem of designing an intervention mechanism for public-interest goods. More specifically, we consider a system composed of a retailer and a central authority that regulates the system through a joint mechanism composed of demand-increasing strategies and rebates. The main goal of the intervention is to encourage the retailer to make decisions that would best benefit the system. By formulating the system via bilevel programming, we do not solely maximize utility, but also consider the retailer's expected profit. We characterize the structure of the solution. We further show that the rebate amount may be independent of investment made in demand-increasing strategies and improvement pattern of mean demand.

In this study, we define expected excess budget that plays a supportive role in decisions to be made. We believe that with stochastic constraints, such quantities should be computed to reflect possible risks in the decisions made.

We attempt to validate the benefits of our model with available data from the California electric vehicle market. The results of the case demonstrate that the joint mechanism brings considerable benefits in terms of utility.

Another important finding of the case study is that the proposed joint mechanism exploits the range of possibilities more extensively, when the problem is solved considering longer horizons. Also, demand variability turns out to be an extremely important factor for the environment considered in the case study. Based on our results, we conclude that approaches that do not consider demand variability may lead to erroneous decisions. This finding is especially apparent in the decision on rebate quantity, as well as in the expected budget that would be required by the central authority.

Note that this modeling framework can be modified for alternative intervention mechanisms, i.e. direct investment affecting any other parameter of the system. This possibility allows the central authority the ability to formulate a bilevel program for each intervention scheme and compare the effect of each scheme. Another improvement can be to represent more than one factor that will change the mean demand, each factor requiring a separate budget. A good example can be depicted from [60]: R&D efficiency is not only a function of research expenditure, but also research manpower. Hence, more realistic representations can be used to replace equations (4.14) and (4.20).

In the following chapter, we examine a special case of *Model JM2-SLP* presented in this chapter to study circumstances where demand is exponentially distributed and demand-increasing strategy has a constant effect on mean demand, and characterize optimal intervention strategy for a new innovative product.

Chapter 5

Joint Intervention Mechanism for a New Innovative Product-Structural Results Under Family of Exponential Demand Functions

5.1 Introduction

In this chapter, we explore the intervention scheme for a new innovative product such as recent developments in green technology. The model we focus on is mainly an adaptation of *Model JM2-SLP*, which is presented in Section 4.3. *Model JM2-SLP* mainly decides on the allocation of budget among two intervention tools, which are demand-increasing strategies and rebates. In the previous chapter, we pose the model without any limitations on the demand distribution, mean demand response function, and utility function. However, here we analyze the model subject to some special cases. We consider the following assumptions: (i) demand is exponentially distributed, (ii) mean demand is a linear function of investment made in demand-increasing strategies, and (iii) objective function is specified as expected sales. Several motivating scenarios can be given for these assumptions. For a new product, the demand is expected to be highly uncertain, thus exponential distribution is a reasonable assumption. Moreover, main goal is to increase adoption level of this type of goods and this objective can be reflected by choosing utility as expected sales.

The remainder of the chapter is organized as follows. In Section 5.2, we present *Model JM2-SLP* under the assumptions described above. In Section 5.3, we derive the optimal solution structure using solution alternatives and KKT conditions and afterwards we analyze the results in Section 5.4. We conclude in Section 5.5 with discussion of results.

5.2 Model

The notation is summarized in Table 5.1 and additional notation is defined and explained as needed. As presented earlier, *Model JM2-SLP* is as follows:

$$\begin{aligned}
\max_{r,B_d,B_r,Q} \quad & g(Q,B_d) \\
\text{s.t.} \quad & B_d + B_r \leq B \\
& r\mathbb{E}[min\{Q,D\}\,|B_d] \leq B_r \\
& r \geq c - p \\
& r \geq 0 \\
& B_d, B_r \geq 0 \\
& F_{B_d}(Q) = \frac{p+r-c}{p+r-s}
\end{aligned}$$

We assume that (i) demand is exponentially distributed; (ii) mean demand is a linear function of investment made in demand-increasing strategies; and (iii) objective function of central authority is specified as expected sales. Under these assumptions, one can recognize that budget constraints will be tight at the optimal solution as shown in Proposition 4.3. In our analysis, we use the mean demand function given by

$$\mu(B_d) = \mu_\infty - d + kB_d, \text{where } \; k \geq 0, \; B_d \leq d/k \tag{5.1}$$

p :	Unit revenue
c :	Unit acquisition cost
s :	Unit salvage price
r :	Unit rebate (given directly to each customer who buys the good)
B_d :	Investment made to demand-increasing strategies
B_r :	Investment made to rebate
B :	Total available budget of central authority
Q :	Order quantity of retailer
$g(.)$:	Utility function of central authority

Table 5.1: Notation

$\mu_\infty - d$ is the initial mean demand and k is a constant reflecting the effectiveness of demand-increasing strategy. Note that there is an upper bound that central authority can invest in demand-increasing strategy, which is d/k and mean demand approaches to μ_∞ at B_d's upper limit.

Q and expected sales can be written explicitly in terms of other variables and parameters for exponential distribution. Specifically, the first order condition of newsvendor problem under exponential distribution with a mean of $\mu(B_d)$ is given by

$$1 - e^{-Q/\mu(B_d)} = \frac{p+r-c}{p+r-s} \tag{5.2}$$

Using Equation (5.2), optimal order quantity and expected sales of retailer can be expressed as follows:

$$Q^* = \mu(B_d) ln \left(\frac{p+r-s}{c-s} \right) \tag{5.3}$$

$$\mathbb{E}[min\{Q^*, D\} | B_d] = \mu(B_d)(1 - e^{-Q^*/\mu(B_d)}) = \mu(B_d)\frac{p+r-c}{p+r-s} \tag{5.4}$$

Then, using (5.3) and (5.4) the problem can be represented as an optimization problem for two variables as follows:

$$
\begin{aligned}
\max_{B_d, r} \quad & \mu(B_d)\frac{p+r-c}{p+r-s} && (5.5)\\
\text{s.t.} \quad & r\mu(B_d)\frac{p+r-c}{p+r-s} - B + B_d = 0 && (5.6)\\
& -r+c-p \leq 0 && (5.7)\\
& -r \leq 0 && (5.8)\\
& -B_d \leq 0 && (5.9)\\
& B_d - d/k \leq 0 && (5.10)
\end{aligned}
$$

5.3 Optimal Solution Structure

In this section, we characterize the structure of the optimal solution depending on the parameters by utilizing the KKT conditions and solution alternatives.

Let λ_i be the multipliers of constraints (5.6) through (5.10) respectively. The KKT conditions imply that in addition to constraints (5.6)-(5.10), the following set of equations should be satisfied:

$$k\left(\frac{p+r-c}{p+r-s}\right) = \lambda_1 rk\left(\frac{p+r-c}{p+r-s}\right) + \lambda_1 - \lambda_4 + \lambda_5 \tag{5.11}$$

$$\mu(B_d)\left(\frac{c-s}{(p+r-s)^2}\right) = \lambda_1\left[\mu(B_d)\left(\frac{p+r-c}{p+r-s}\right) + r\mu(B_d)\left(\frac{c-s}{(p+r-s)^2}\right)\right] - \lambda_2 - \lambda_3 \tag{5.12}$$

$$\lambda_2 r = 0 \tag{5.13}$$

$$\lambda_3(-p+c-r) = 0 \tag{5.14}$$

$$\lambda_4 B_d = 0 \tag{5.15}$$

$$\lambda_5(B_d - d/k) = 0 \tag{5.16}$$

$$\lambda_2, \lambda_3, \lambda_4, \lambda_5 \geq 0 \tag{5.17}$$

$$\lambda_1 \;\; free \tag{5.18}$$

The solution alternatives for the formulation given by (5.5)-(5.10) can be listed as follows:

A1. $B_d = 0$ and $r \geq 0$

A2. $B_d = d/k$ and $r > 0$

A3. $0 \leq B_d \leq d/k$ and $r = 0$

A4. $0 \leq B_d \leq d/k$ and $r > 0$

Note that the linear independence constraint qualification holds for each solution alternative. Thus, KKT conditions are necessary for optimality. Hereafter, we analyze the KKT system for each solution alternative one at a time.

A1. $\mathbf{B_d = 0}$ **and** $\mathbf{r \geq 0}$:

One can find the optimal value of r for this case by solving the quadratic equation given below, which is obtained by substituting value of $B_d = 0$ into constraint (5.6):

$$r(\mu_\infty - d)\left(\frac{p+r-c}{p+r-s}\right) - B = 0. \tag{5.19}$$

Equivalently, $r^2(\mu_\infty - d) + r[(\mu_\infty - d)(p-c) - B] - B(p-s) = 0.$

The roots of this equation are given by, $r = \frac{(\mu_\infty - d)(c-p)+B \pm \sqrt{[(\mu_\infty - d)(p-c)-B]^2 + 4(\mu_\infty - d)B(p-s)}}{2(\mu_\infty - d)}$. Note that for both $r \geq c-p$ (i.e. corresponds to $c > p$) and $r \geq 0$ (i.e. corresponds to $p > c$), the following root is valid:

$$r_{A1} = \frac{(\mu_\infty - d)(c-p) + B + \sqrt{[(\mu_\infty - d)(p-c) - B]^2 + 4(\mu_\infty - d)B(p-s)}}{2(\mu_\infty - d)}. \tag{5.20}$$

Since KKT conditions are necessary for optimality, r_{A1} is the value of unique optimum for this alternative solution. Note that the optimal values of Lagrange multipliers for this alternative are as follows:

$$\lambda_2 = \lambda_3 = \lambda_5 = 0$$
$$\lambda_1 = \frac{c-s}{(p+r-c)(p+r-s)+r(c-s)}$$
$$\lambda_4 = \lambda_1 rk\left(\frac{p+r-c}{p+r-s}\right) + \lambda_1 - k\left(\frac{p+r-c}{p+r-s}\right)$$

KKT conditions indicate that $\lambda_4 \geq 0$, and it is true for $B \leq B_t^1$, where $B_t^1 = \frac{(\mu_\infty - d)[(c-p)+\sqrt{\frac{(c-s)}{k}}]}{1+\sqrt{(c-s)k}}$.

The optimal solution for this case will be $(B_d^* = 0, r^* = r_{A1})$

A2. $\mathbf{B_d = d/k}$ and $\mathbf{r > 0}$:

Similar with the previous alternative, the optimal values of r can be found by substituting $B_d = d/k$ into constraint (5.6) and solving for r.

$$r\mu_\infty\left(\frac{p+r-c}{p+r-s}\right) - B + d/k = 0.$$

Equivalently, $r^2\mu_\infty + r[\mu_\infty(p-c) - B + d/k] - (B - d/k)(p-s) = 0.$

The roots of this equation are given by, $r = \frac{\mu_\infty(c-p)+B-d/k \pm \sqrt{[\mu_\infty(p-c)-B+d/k]^2+4\mu_\infty(B-d/k)(p-s)}}{2\mu_\infty}$. Note that for both $r \geq c-p$ (i.e. corresponds to $c > p$) and $r \geq 0$ (i.e. corresponds to $p > c$) only one of the roots is valid, which is:

$$r_{A2} = \frac{\mu_\infty(c-p)+B-d/k+\sqrt{[\mu_\infty(p-c)-B+d/k]^2+4\mu_\infty(B-d/k)(p-s)}}{2\mu_\infty}. \tag{5.21}$$

r_{A2} is the value of unique optimum for this alternative solution, because KKT conditions are necessary for optimality. The values of Lagrange multipliers for this alternative are:

$$\lambda_2 = \lambda_3 = \lambda_4 = 0$$
$$\lambda_1 = \frac{c-s}{(p+r-c)(p+r-s)+r(c-s)}$$
$$\lambda_5 = k\left(\frac{p+r-c}{p+r-s}\right) - \lambda_1 rk\left(\frac{p+r-c}{p+r-s}\right) - \lambda_1$$

KKT conditions indicate that $\lambda_5 \geq 0$, and it is true for $B \geq B_t^2$, where $B_t^2 = \frac{d}{k} + \frac{\mu_\infty[(c-p)+\sqrt{\frac{(c-s)}{k}}]}{[1+\sqrt{(c-s)k}]}$.

The optimal solution for this case will be $(B_d^* = d/k, r^* = r_{A2})$

A3. $\mathbf{0 \leq B_d \leq d/k}$ **and** $\mathbf{r = 0}$ (only realized when $p > c$) :

It is obvious that, $B_{dA3} = B$ for this case. The values of Lagrange multipliers can be given as follows:

$$\lambda_3 = \lambda_4 = \lambda_5 = 0$$
$$\lambda_1 = \left(\frac{p-c}{p-s}\right)$$
$$\lambda_5 = \frac{\mu(B_d)}{(p-s)^2}[k(p-c)^2 - (c-s)].$$

KKT system implies that $\lambda_2 \geq 0$, and this is true if $k \geq k_t = \frac{(c-s)}{(p-c)^2}$.

The optimal solution for this case will be $(B_d^* = B, r^* = 0)$

A4. $\mathbf{0 < B_d \leq d/k}$ **and** $\mathbf{r > 0}$

Using Equation (5.6), we can represent B_d in terms of r, which is given below:

$$B_d = \frac{B(p+r-s) - r(p+r-c)(\mu_\infty - d)}{rk(p+r-c)+(p+r-s)}$$

By substituting the value of B_d into objective function, we can express the objective function in terms of r. We have:

$$
\begin{aligned}
\max_{r} \quad & \left(\mu_\infty - d + \frac{kB(p+r-s) - kr(p+r-c)(\mu_\infty - d)}{rk(p+r-c)+(p+r-s)}\right)\left(\frac{p+r-c}{p+r-s}\right) \\
\text{s.t.} \quad & r \geq 0 \\
& r \geq c-p
\end{aligned}
$$

We apply the first order condition on the objective function with respect to r, and find out two possible values for r as follows, $r = c - p \pm \sqrt{\frac{c-s}{k}}$. One can show that only one of the value is valid, which is given below:

$$
r_{A4} = c - p + \sqrt{\frac{c-s}{k}}. \tag{5.22}
$$

For $r \geq 0$ the following condition on k should hold: $k \leq k_t = \frac{c-s}{(p-c)^2}$.

Note that second derivative of the objective function is always negative at r_{A4}, which guarantees that it is the unique maximizer. Next, we express the optimal value of B_d in terms of problem parameters by substituting optimal value of r and we obtain:

$$
B_{dA4} = \frac{B[(c-s)k + \sqrt{(c-s)k}] + [(p-c)\sqrt{(c-s)k} - (c-s)](\mu_\infty - d)}{[(c-s)k + \sqrt{(c-s)k}] + [(c-s) - (p-c)\sqrt{(c-s)k}]k} \tag{5.23}
$$

Note that the following conditions on B should be ensured so that non-negativity constraint and upper bound constraint on B_d hold.

$$
B_t^1 \leq B \leq B_t^2
$$

$$
\text{where } B_t^1 = \frac{(\mu_\infty - d)[(c-p)\sqrt{(c-s)k} + (c-s)]}{(c-s)k + \sqrt{(c-s)k}} \tag{5.24}
$$

$$
B_t^2 = \frac{[(c-s)k + \sqrt{(c-s)k}]d + [(c-s) - (p-c)\sqrt{(c-s)k}]\mu_\infty k}{[(c-s)k + \sqrt{(c-s)k}]k} \tag{5.25}
$$

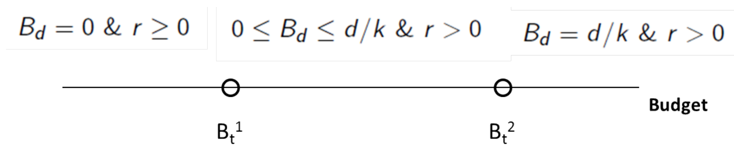


Figure 5.1: Optimal solution structure for $c \geq p$

In a simplified form:

$$B_t^1 = \frac{(\mu_\infty - d)[(c-p) + \sqrt{\frac{(c-s)}{k}}]}{1 + \sqrt{(c-s)k}} \leq B \leq B_t^2 = \frac{d}{k} + \frac{\mu_\infty[(c-p) + \sqrt{\frac{(c-s)}{k}}]}{[1 + \sqrt{(c-s)k}]}$$

Therefore, this solution alternative will arise when $B_t^1 \leq B \leq B_t^2$, and optimal solution will be $(B_d^* = B_{dA4}, r^* = r_{A4})$.

The optimal values corresponding to intervention tools are given below each solution alternative. Notice that the alternatives are valid only in certain ranges, which are defined in terms of k and B. Next, we characterize the solution structure for two different parameter settings: (i) $c \geq p$ and (ii) $c < p$, separately.

5.3.1 Case 1: $c \geq p$

The solution alternatives that may appear for this case are A1, A2, and A4. The optimal solution structure is illustrated in Figure 5.1 and also it can be represented as follows:

$$(B_d^*, r^*) = \begin{cases} (0, r_{A1}) & \text{B} \leq B_t^1 \\ (B_{dA4}, r_{A4}) & \text{if } B_t^1 \leq B \leq B_t^2 \\ (d/k, r_{A2}) & \text{if B} \geq B_t^2 \end{cases}$$

where B_t^1 and B_t^2 are given by (5.24) and (5.25), respectively.

5.3.2 Case 2: $p > c$

Figure 5.2 shows the optimal solution structure in the defined ranges for this case and the optimal solution in terms of parameters can be summarized as follows:

$$(B_d^*, r^*) = \begin{cases} (0, r_{A1}) & \text{if B} \leq B_t^1, k \leq k_t \\ (B_{dA4}, r_{A4}) & \text{if } B_t^1 \leq B \leq B_t^2, k \leq k_t \\ (B, r_{A3}) & \text{if } B \leq d/k, k \geq k_t \\ (d/k, r_{A2}) & \text{ow} \end{cases}$$

where B_t^1 and B_t^2 are given by (5.24) and (5.25), respectively.

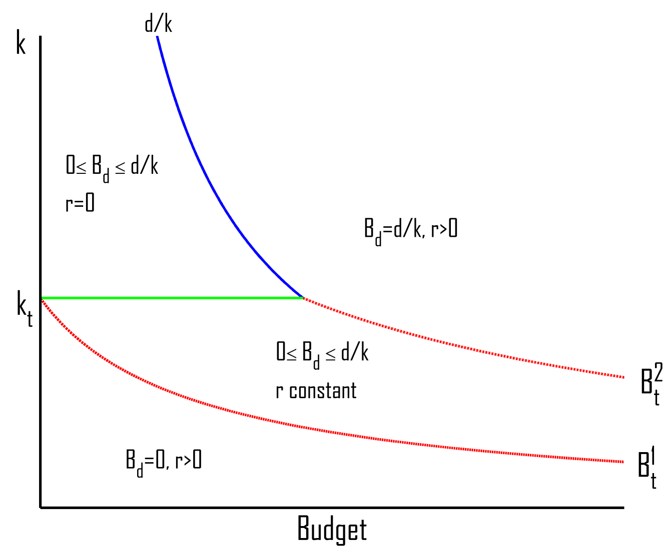


Figure 5.2: Optimal solution structure for $p > c$

5.4 Analysis of Results

5.4.1 General Results

Figure 5.3 shows the effect of budget on the optimal solution, B_d^*, r^*, Q^*, and expected sales, respectively, when $c \geq p$. As expected, Q^* and expected sales increase with the increase in budget. Regarding B_d^*, it is zero until budget threshold B_t^1; then increases between B_t^1 and B_t^2 up to its upper limit d/k; and then it stays constant at d/k. For r^*, it increases up to B_t^1; and stays constant between B_t^1 and B_t^2; and continues to increase after B_t^2.

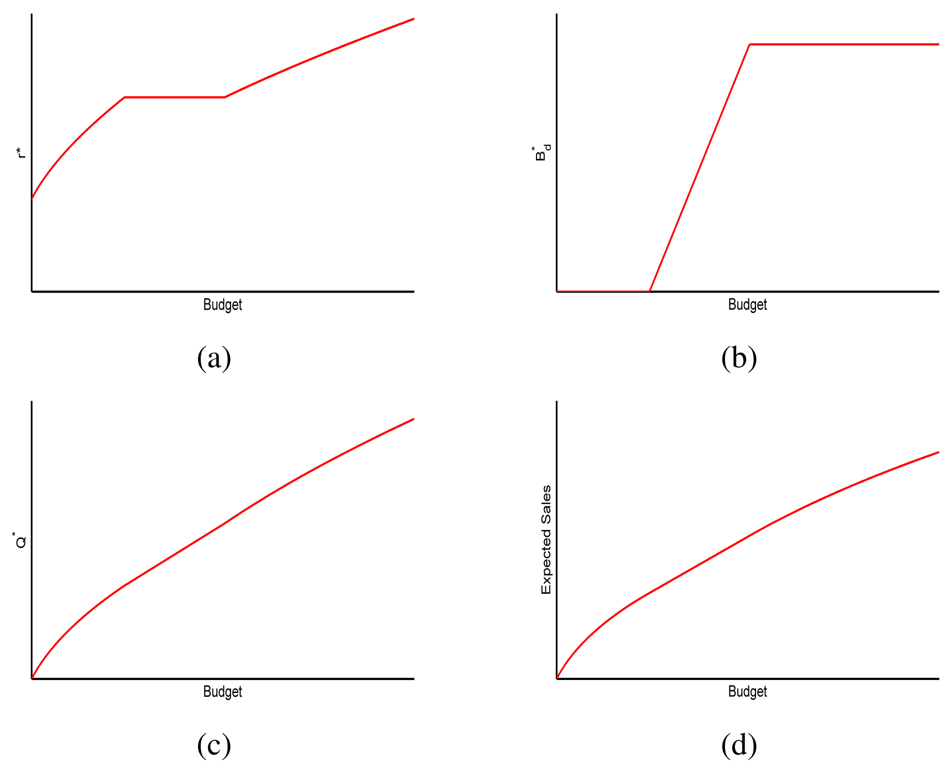


Figure 5.3: Budget vs optimal solution for $c \geq p$

Similarly, Figures 5.4 and 5.5 present the change of optimal solution with respect to budget, when $p > c$. For both $k \geq k_t$ and $k < k_t$ cases, as budget increases, Q^* and expected sales increase. When $k < k_t$, r^* and B_d^* show a similar trend with respect to change in budget as in $c \geq p$ case. For $k \geq k_t$, $r^* = 0$ and B_d^* is increasing up to a budget of d/k; and when budget is above d/k, $B_d^* = d/k$ and r^* is increasing with the increase in budget.

Solution structures for both $c \geq p$ and $p > c$ cases show that if $B_t^1 \leq B \leq B_t^2$ fixed rebate amount will be administered irrespective of budget amount. For the case when $p > c$, if demand-increasing strategy has a remarkable effect on society or in other words efficiency of demand-increasing strategy (k) is high, central authority will only invest in this strategy up to a certain budget threshold.

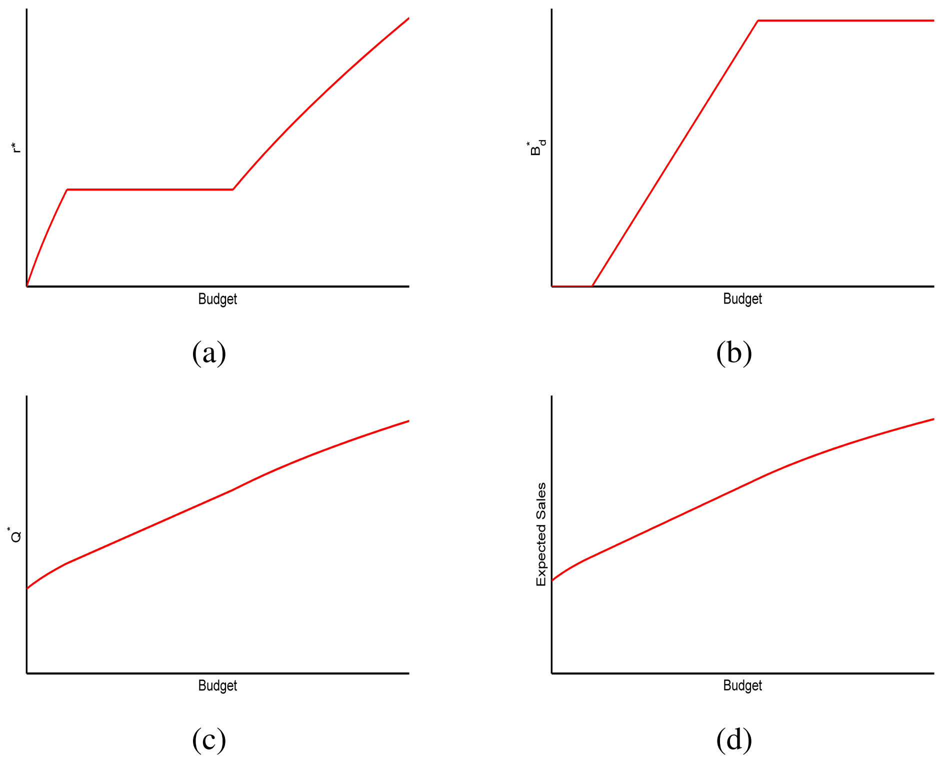


Figure 5.4: Budget vs optimal solution for $p > c$ and $k < k_t$

5.4.2 Expected Profit of Retailer

Optimal expected profit of the retailer is given as:

$$E[P(Q^*)] = \mu(B_d)\left[(p+r-c)+(c-s)ln\left(\frac{c-s}{p+r-s}\right)\right]. \tag{5.26}$$

As expected, expected profit wise retailer is always better off under intervention mechanism. Figure 5.6 includes plots for expected profit with respect to budget for the case $p \leq c$ and $p > c$, respectively. Note that budget thresholds B_t^1 and B_t^2 have different values for the two parameter settings. As seen from the figures, expected profit of retailer increases incrementally as a function of budget for both of the cases. However, the magnitude of increase differs under two different parameter settings. To gain insight about optimal budget level of central authority, it is useful to analyze expected profit of retailer in comparison with the budget amount reserved by the central authority. Plots show that the best budget interval to operate for the central authority is the one that assigns fixed rebate to the retailer (i.e. $B_t^1 \leq B \leq B_t^2$). The reason behind

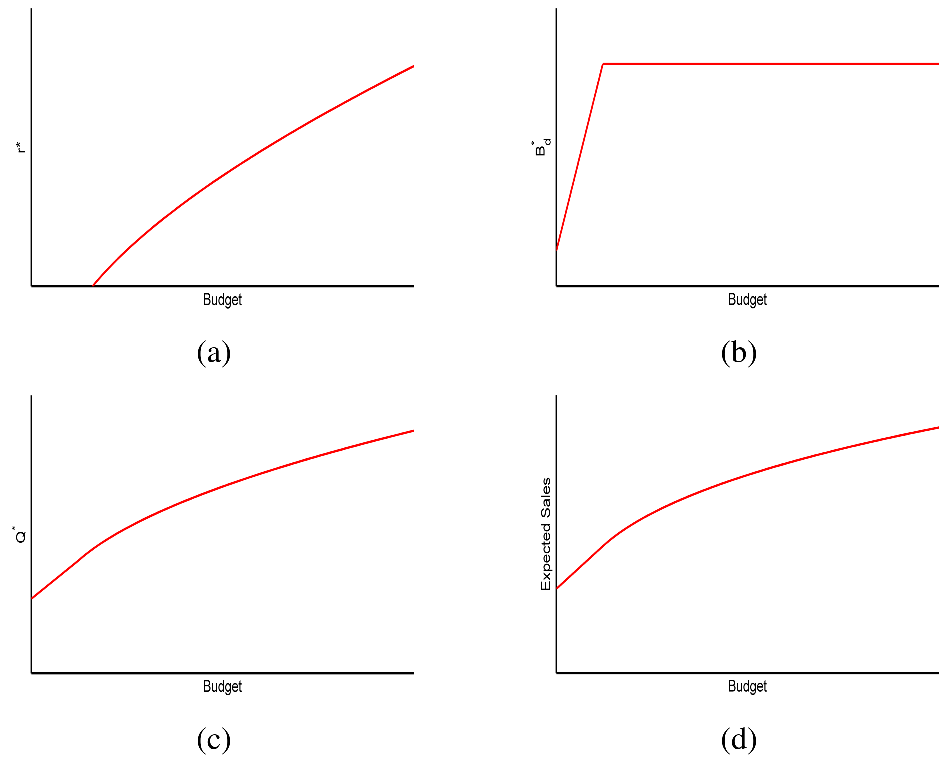


Figure 5.5: Budget vs optimal solution for $p > c$ and $k \geq k_t$

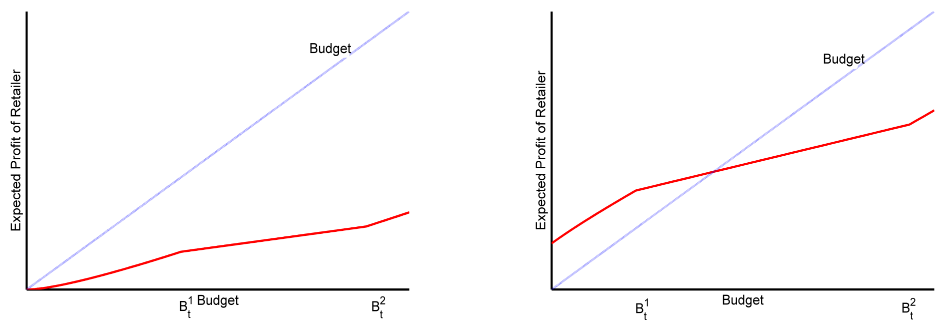
this is that when $B > B_t^2$, the intervention turns out to be money transfer to the retailer. Thus, increasing the budget amount after this threshold is gainless. Thus, strategies that will trigger competition would be more reasonable after this threshold budget level.

5.4.3 Expected Excess Budget Required

We define expected excess budget required as in Subsection 4.5.4.2 of Chapter 4. Under exponential distribution with constant demand-increasing strategy effect, expected excess budget required becomes:

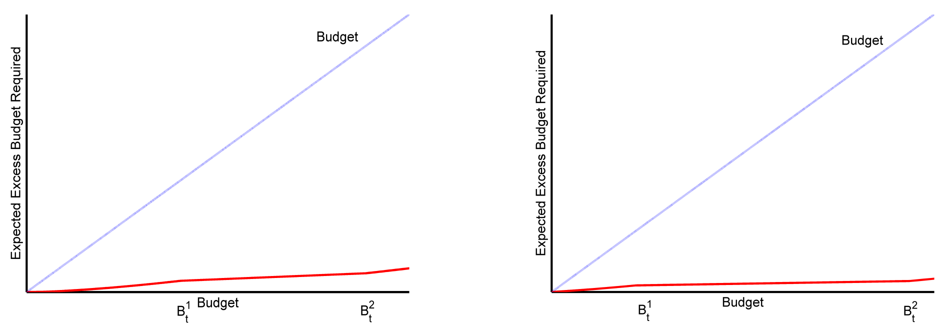
$$\mathbb{E}[EB] = r(\mu_\infty - d + kB_d)\left(e^{-\left(\frac{p+r-c}{p+r-s}\right)} - \frac{c-s}{p+r-s}\right) \tag{5.27}$$

Figure 5.7 plot expected excess budget required as a function of budget for cases $p \leq c$ and $p > c$, respectively. As in the plots of expected profit, budget thresholds B_t^1 and B_t^2 are different for the two parameter settings. Recall that expected excess budget amount can be interpreted as the risk of implementing intervention mechanism from central authority's point of view. The calculated expected excess budget amounts are lower than the available budget amount of central authority. Besides, plots indicate that magnitude of expected excess budget is growing increasingly when budget is higher than B_t^2. The risk associated with expected excess budget amount indicates that it is not reasonable to operate with a budget higher than B_t^2 for the central authority.



(a)$p \leq c$ (b)$p > c$

Figure 5.6: Expected Profit of Retailer



(a)$p \leq c$ (b)$p > c$

Figure 5.7: Expected Excess Budget Required

5.5 Concluding Remarks

In this chapter, we study the problem of designing an intervention mechanism for a new innovative product. We figure out that use of a fixed rebate without considering budget as in current practices may lead to remarkable budget deficits. In addition, increasing the rebate amount after a certain budget level may result in excess money transfer to retailers. One can show that demand-increasing strategies may yield better utilities than rebates depending on the budget value. Thus, we can conclude that if we ignore budget constraint while designing intervention mechanism we most likely lose efficiency and effectiveness.

Chapter 6

Joint Intervention Mechanism In the Presence of Yield Uncertainty

In this chapter, we explore the intervention design problem for a public-interest good facing yield uncertainty in production.

6.1 Introduction

The motivation of this study is based on influenza vaccine supply chain. Influenza is a very well-known acute respiratory illness that circulates quickly resulting in seasonal outbreaks. World Health Organization (WHO) reports that each year the outbreaks end up with 250,000 to 500,000 deaths globally; additionally annual costs of outbreaks in terms of health care, lost days of work and schooling, and social disruption vary between $1 million and $6 million per 100,000 inhabitants in industrialized countries like France, Germany, and the United States [61]. Annual vaccination is known to be the most effective and efficient strategy for fighting influenza to prevent morbidity and mortality. Therefore, majority of the countries carry out influenza vaccination programmes targeting nationwide coverage levels. In spite of the programmes having been implemented, current statistics show that the vaccine coverage lag behind the targeted goals in most of the developed countries [6, 7]. Also, WHO reports that all countries in the world are facing influenza vaccine shortage. These problems originate from issues that are inherent to influenza vaccine supply chains.

One of the challenges of this system arises mainly due to characteristics of production process such as long production times, reformulation of vaccine composition each year, and yield issues. Majority of the production depends on flu virus grown in chicken eggs. The process starts with the announcement of the WHO Global Influenza Program on the virus strains that will be included in the forthcoming season's vaccines. The manufacturing procedure takes approximately six months and can be summarized as follows: growing the virus in chicken eggs, harvesting the virus containing fluid from the eggs after several days, inactivating viruses, purifying, testing, and packaging [62]. Vaccine composition is controlled each year and updated if needed due to continuous antigenic changes in the virus strains. The uncertain growth characteristics of strains in chicken eggs causes yield uncertainty, i.e. either the production may result in fewer quantities or it may need extra time to end up with desired quantities [63].

Another problem is insufficient demand for reaching an effectual or socially desirable coverage level. The reasons behind this are free-rider phenomenon (negative network externality effect) and lack of incentives. Individual's decisions on whether to uptake vaccine may be influenced by the decisions of the rest of the society. Vaccines enable individuals to receive benefits of other's vaccination without a payment (free-ride), because individuals are aware that vaccination reduces the probability of transmission.

The focus of this chapter is designing an intervention strategy for influenza vaccines, which will decrease the effects of inefficiencies described above and encourage the channel to take a solution closer to socially optimal decision. In the strategy, we consider possibility of different efforts that will eventually increase the production quantity. We enable this by considering a total budget, which can be used for different efforts, and solve a budget allocation problem.

The production processes in many industries face yield uncertainty such as agriculture, biofuel production, mining, and etc. Note that although the framework of the study is inspired from influenza vaccines, it can be applied to other goods with similar characteristics. Throughout the chapter, we study the problem for a system consisting of a newsvendor firm that faces yield issues and a central authority having a fixed budget. Relating with the influenza vaccine case, newsvendor firm corresponds to a vaccine manufacturer, whereas central authority refers to a social planner like WHO, Centers for Disease Control and Prevention (CDC), etc. or a government. The role of the central authority is to coordinate the expenditures limited by the budget and maximize the social welfare. A critical issue while designing an intervention mechanism is to choose the intervention tools to be considered and their associated effects.

One alternative is making investment to demand-increasing strategies. We assume that this investment is devoted to any attempt that will promote vaccination. In practice, these may correspond to subsidizing vaccine cost, public education, media campaigns to inform those at high risk, expanding access to vaccination services (i.e. via pharmacy, immunization centers near schools and worksites, home visits), organizing school vaccination programs, and establishing client reminder and recall systems [7]. A different example to demand-increasing strategies can be given based on a recent news discussing low immunization rates for HPV [64]. Current policy issues and lack of MD endorsement (and recommendation) are found to be responsible for the shortfall in the usage of these vaccines. For this case mentioned in the news, organizing information briefing for doctors can be a good example for demand-increasing strategies so that they will make timely recommendations to children for receiving the vaccine.

Another intervention tool is yield increasing strategy through which production yield will be improved. Current production technologies of flu vaccines have several limitations like yield issues, production capacity, and ability to accelerate production in case of pandemics. These inefficiencies can be overcome through financial support to manufacturer to increase yield and improve availability. Deo and Corbett [24] highlight that it is required to subsidize research on production processes instead of only implementing immunization programs that encourage vaccination.

In brief, we analyze an intervention mechanism composed of the two intervention tools described above. We note that the proposed joint mechanism's objectives are parallel with the objectives of GAP (Global action plan for influenza vaccines), which is carried on by WHO [65]. GAP is an exhaustive project aimed at achieving higher vaccine usage, improving production capacity, and research and development.

Unlike the existing studies in the literature, our model is a budget allocation problem and further decides on the quantity to be produced and intervention scheme under both demand and yield uncertainty. Also, our work is differentiated from previous work in terms of intervention tools considered and their effects on the system dynamics. We do not take into account epidemiological details and this makes this framework applicable to other types of goods with similar characteristics.

To analyze the above mentioned framework, we build a bilevel programming model, which enables us to integrate manufacturer's point of view into the central authority's decision making process. We assume that demand and yield are correlated random variables without loss of generality and follow bivariate lognormal distribution. Bivariate lognormal distribution is quite general as one can represent distributions with various values for coefficient of variation. We express demand and yield as functions of corresponding investments made to improve them. Under the lognormal demand and yield models proposed, given central authority's decisions we obtain closed form expression for the optimal quantity to be produced by the manufacturer. We also characterize the optimal solution for specific forms of authority's objective function, and demand and yield functions. We complete our presentation with numerical experiments. The numerical experiments rely on available estimates from studies on influenza vaccine supply chains in literature and CDC's statistics on flu vaccination coverage in US. We propose a parameter calibration procedure based on available information. Our results indicate that proposed joint mechanism challenges the current policy including only demand-increasing strategies in two dimensions: vaccination coverage and budget required. Moreover, we compare the results with the case where yield is approximated by a deterministic function dependent on investment made to improve it. The solutions show that the vaccination coverage obtained with deterministic yield function are very close to the ones achieved under yield uncertainty if the demand function's parameters are calibrated accurately for each version. Finally, we add a discussion and our findings on the selection of total budget level to support decision makers.

6.2 Model and Assumptions

This section presents demand and yield models, and the decision model to determine the allocation of budget among intervention tools.

6.2.1 Representation of Demand and Yield

We use lognormal distribution for demand and yield because it is flexible in terms of providing various forms of distribution with two parameters.

We assume that demand comes from a family of lognormal distributions with parameter B_d. To represent it we define a lognormal demand function dependent on B_d. Once B_d is set, the demand distribution will be known accordingly.

$$D = H_D(B_d)e^{-\frac{1}{2}\sigma_D^2+\sigma_D W_D},$$

where W_D has standard normal distribution and σ_D is a parameter of the distribution. It can be verified that $E[D] = H_D(B_d)$, where $H_D(B_d)$ is a function of B_d, and $Var(D) = H_D(B_d)^2(e^{\sigma_D^2} - 1)$. The mean and variance change in a proportional fashion with respect to B_d, thus coefficient of variation is preserved (i.e. cv_D=$\sqrt{e^{\sigma_D^2} - 1}$).

Remark 6.1 *If $H_D(B_d)$ is an increasing function of B_d, there will be a first order stochastic dominance order between cdfs of demand. Specifically, the cdf with higher B_d value will stochastically dominate all others with smaller B_d.*

We model yield uncertainty with stochastically proportional yield approach, which is widely studied in the literature (i.e. see [66] for a detailed review of approaches solving lot sizing problem with random yield). This approach is applicable to systems like influenza vaccine production system, in which yield uncertainty emanates from inflexibility of production system to adapt to changes in the environment or material.

We construct the yield function with a similar reasoning as in demand function. We use a lognormal yield function dependent on parameter B_y.

$$Y = H_Y(B_y)e^{-\frac{1}{2}\sigma_Y^2+\sigma_Y W_Y},$$

where W_Y has standard normal distribution and σ_Y is a parameter of the distribution. As in the demand function, $E[Y] = H_Y(B_y)$, where $H_Y(B_y)$ is an increasing concave function in B_y and takes values in the interval [0,1], and $Var(Y) = H_Y(B_y)^2(e^{\sigma_Y^2} - 1)$. Similarly, coefficient of variation is independent of B_y (i.e. cv_Y= $\sqrt{e^{\sigma_Y^2} - 1}$). Furthermore, note that similar to Remark 6.1 first order stochastic dominance order holds for the yield model.

We assume that demand and yield are jointly lognormally distributed. Specifically, natural logarithms of random variables D and Y have bivariate normal distribution with means $ln(H_D(B_d)) - \sigma_D^2/2$ and $ln(H_Y(B_y)) - \sigma_Y^2/2$, and standard deviations σ_D and σ_Y, respectively, and correlated by ρ. Specifically, (W_D, W_Y) has a standard bivariate normal distribution with correlation coefficient ρ, $E[W_D, W_Y] = \rho$.

In our model, B_d denotes the investment amount allocated to demand-increasing strategies, whereas B_y reflects the investment amount allocated to yield increasing strategies. Any effort targeted to achieve higher demand attracts more consumers for vaccine uptake and thus shifts the mean demand upwards. Besides, investment devoted to yield increasing strategies decreases the risks included in the manufacturing process and improves the yield. Thus, an increase in the investment amounts B_d or B_y leads to a first order stochastic dominance order between cdfs of demand or yield, respectively as described in Remark 6.1. Note that we can also envision a correlation between the uncertain components of demand and yield variables. Positive correlation indicates that higher demand motivates the manufacturer to improve yield. On the other hand, negative correlation can be explained by prevention of artificial demand amplification through a more successful production.

In the later sections of the chapter, we assume specific forms for $H_D(B_d)$ and $H_Y(B_y)$. Although there are not many studies on investment response functions, an advertising response function is generally assumed to be concave in advertising expenditure in previous studies (e.g. [48, 49, 50]), and we follow the same assumption in our analysis. Under a concave response function, as the money invested increases the mean demand and mean yield also increase but with a monotonically diminishing rate. In our analysis, we use the mean demand function analyzed in [48], which is given below:

$$H_D(B_d) = \mu + \mu w B_d^{\alpha}$$

where μ is the initial mean demand (i.e. mean demand before intervention), and w and α ($0 \leq \alpha \leq 1$) are constants that reflect effectiveness of demand-increasing strategy. For a fixed $w > 0$, mean demand increases at a faster rate for larger values of α. When $w = 0$, mean demand is not influenced by demand-increasing strategies.

One possible form for $H_Y(B_y)$ is as follows:

$$H_Y(B_y) = \tfrac{kB_y+1}{kB_y+a}, \text{ for } a > 1 \text{ and } k > 0.$$

As $B_y \to 0,\ H_Y(B_y) \to \frac{1}{a}$ and as $B_y \to \infty,\ H_Y(B_y) \to 1.$ $1/a$ gives the initial yield (yield rate without intervention) and k is a measure for the efficiency of the yield improving technology.

6.2.2 Decision model

We model intervention design problem for the context discussed by bilevel programming. Similar to previous chapters, the central authority is the leader, who is interested in maximizing the social welfare, whereas newsvendor firm is the follower with the objective of maximizing expected profit. Central authority intervenes in the system through a joint mechanism composed of two intervention tools: (i) investment made in demand-increasing strategies, B_d, and (ii) investment made in yield improving strategies, B_y. Any effort aimed at increasing demand will shift the demand distribution, and similarly investment made in yield increasing strategies will affect yield distribution.

We assume that the social welfare is assessed by an increasing concave function of production quantity, which in turn is a function of the intervention mechanism (i.e. B_d and B_y).

Let p, c, s be unit selling price, manufacturing cost, and salvage value respectively. $u(.)$ denotes the utility function that is dependent on the production quantity Q, and assumed to be concave in its arguments for detailed analysis. The bilevel programming formulation of the problem (BLP) is as follows:

$$\max_{B_d, B_y} \quad u(Q(B_d, B_y)) \tag{6.1}$$

$$\text{s.t.} \quad B_d + B_y \leq B \tag{6.2}$$

$$B_d, B_y \geq 0 \tag{6.3}$$

$$\max_Q E[P(Q)]. \tag{6.4}$$

where $P(Q)$ is the profit function of the newsvendor firm and is given by:

$$P(Q) = pYQ1_{\{YQ \leq D\}} + rD1_{\{YQ \geq D\}} + s(YQ - D)1_{\{YQ \geq D\}} - cQ$$

with $1_A = 1$ if A is true, and 0 otherwise. Note that we explore the model for stochastically proportional yield, that is the quantity that will be received at the end of manufacturing process is YQ.

In this problem, the central authority goes first and determines the investment amounts made to intervention tools, and later in view of his decisions manufacturer decides on production quantity. (6.1)-(6.3) express the upper level (central authority's) problem, while (6.4) corresponds to the lower level (manufacturer's) problem. The objective of the central authority is to find the utility maximizing investment amounts, B_d and B_y. The selection of B_d and B_y affects the solution and objective function of the manufacturer by affecting the distributions used to evaluate $P(Q)$, and in turn manufacturer's decision influences the central authority's utility. Constraint (6.2) imposes budget constraint on the total money invested for demand-increasing activities, and research and development. (6.3) guarantees non-negativity of B_d and B_y. Lastly, (6.4) reflects the newsvendor problem under random supply for given B_d and B_y.

6.2.3 Solution

6.2.3.1 Analysis of lower level problem:

Primary approach for solving bilevel optimization problems is replacing lower level problem by its first order conditions. Thus, we start our analysis by lower level problem.

We find out that the expected profit maximizing Q occurs at

$$E[Y1_{\{D\leq YQ\}}] = \frac{pE[Y]-c}{p-s}. \tag{6.5}$$

The details of derivation can be found in Appendix C.1.

We use the properties of lognormal random variables to derive $E[Y1_{\{D\leq YQ\}}]$. Theorem 2.1 of [67] gives an explicit expression for moments of the form $E[X^mY^nI_{XY}(a,b,K)]$, where $(X,Y)^T$ have bivariate lognormal distribution and $I_{XY}(a,b,K)$ is an indicator function which takes value of 1 when $X^aY^b \leq K$ and 0 otherwise. After applying this theorem to our case, we obtain the following form:

$$E[Y1_{\{D\leq YQ\}}] = H_Y(B_y)\Phi\left(\frac{ln(Q)+ln(H_Y(B_y))-ln(H_D(B_d))+\sigma_Y^2/2+\sigma_D^2/2-\rho\sigma_Y\sigma_D}{\sqrt{\sigma_Y^2+\sigma_D^2-2\rho\sigma_Y\sigma_D}}\right) \tag{6.6}$$

Solving (6.5)-(6.6) for Q, we come up with:

$$Q = e^{[\Phi^{-1}(\frac{pH_Y(B_y)-c}{(p-s)H_Y(B_y)})\sqrt{\sigma_Y^2+\sigma_D^2-2\rho\sigma_Y\sigma_D}-\ln(H_Y(B_y))+\ln(H_D(B_d))-\sigma_Y^2/2-\sigma_D^2/2+\rho\sigma_Y\sigma_D]}, \tag{6.7}$$

where $\Phi^{-1}(.)$ denotes the inverse of the standard normal cdf.

Remark 6.2 *Along with the fact that the argument of $\Phi^{-1}(.)$ should be between 0 and 1, we deduce the following conditions on $H_Y(B_y)$ from (6.7):*

$$H_Y(B_y) > \frac{c}{p}, \tag{6.8}$$

$$H_Y(B_y) < \frac{c}{s}. \tag{6.9}$$

The second condition is readily satisfied by the assumptions of the newsvendor problem and definition of the $H_Y(B_y)$. Thus, it is critical to check whether the condition given by equation (6.8) is always satisfied or not while solving the model.
For the specific form $H_Y(B_y) = \frac{kB_y+1}{kB_y+a}$, this condition is always satisfied if $p > ac$. Actually, this condition on the model parameters is a natural assumption for the newsvendor so that it is economic to operate. In other words, it guarantees that revenue is higher than the average cost. In the opposite case (if $p < ac$), the intervention mechanism is able to make the system economic by investing on yield increasing strategies, and consequently increasing the yield. Note that in this case, there is a minimum budget requirement constraint for B_y, i.e. $B_y > \frac{ac-p}{k(p-c)}$, that will enable the manufacturer to operate.

6.2.3.2 Analysis of the problem:

Remark 6.3 *For given B_d and B_y, the solution for the lower level problem (equation (6.7)) is unique, implying that the rational reaction set is single valued and unique.*

Remark 6.4 *Following Remark 6.3, the uniqueness of the reaction set (lower level problem) guarantee that the leader achieves his maximum objective (by Proposition 8.1.1 pg. 303 [5]).*

Lemma 6.1 *$E[P(Q)]$ is concave in Q for every B_d and B_y. This assures that the solution to the lower level problem is unique, implying that the lower level problem can be replaced by its first order condition (by pg. 308 of [5]).*

Accordingly, (BLP) can be written as the following single-level mathematical program (SP):

$$\max_{B_d, B_y} \quad u(Q(B_d, B_y)) \tag{6.10}$$

$$\text{s.t.} \quad B_d + B_y \leq B \tag{6.11}$$

$$B_d, B_y \geq 0 \tag{6.12}$$

$$(6.7) \tag{6.13}$$

Now, we obtain a relatively easy to solve standard nonlinear program. In this formulation, the central authority optimizes utility (social welfare) subject to her constraints and optimal decision of manufacturer.

Proposition 6.1 *All of the budget will be used at the central authority's optimal intervention scheme, i.e.* $B_d^* + B_y^* = B$ *holds at the optimal solution* (Q^*, B_d^*, B_y^*).

Proof: *See Appendix C.1.*

Remark 6.5 *If* $\sqrt{\sigma_Y^2 + \sigma_D^2 - 2\rho\sigma_Y\sigma_D} > 0.3989\left(\frac{p-s}{c}\right)$ *, then* $\frac{\partial Q}{\partial B_y} > 0$.

Proof: *See Appendix C.1.*

Remark 6.5 states a sufficient condition to ensure an increase in B_y will in turn increase Q. However, at the same time, it implies that when uncertainty is low or when the system is very profitable, yield increasing strategies may have no effect or negative effect on Q. Note that this does not necessarily mean that expected sales is decreasing. Figure 6.1 depicts an example for this case. Briefly, the figure illustrates optimal manufacturing quantity and expected sales as a function of B_y for a given value of B_d. The intuition is that the improvement in yield does not necessarily imply an increase in targeted quantity, Q^*, since the realized quantity will be more by manufacturing with a higher yield.

6.2.4 Further results when utility function is expected sales

Motivated by the vaccine markets environment, we use the expected sales value to assess the utility for this problem. Note that one can use any objective function that will reflect societal benefit. The governments' or social planner's main goal is to reach (or get closer to) socially optimal level of vaccine coverage, which is usually stated as a coverage rate. Therefore, for budgets that are not extremely large the expected sales will be a realistic objective function consistent with the current market environment.

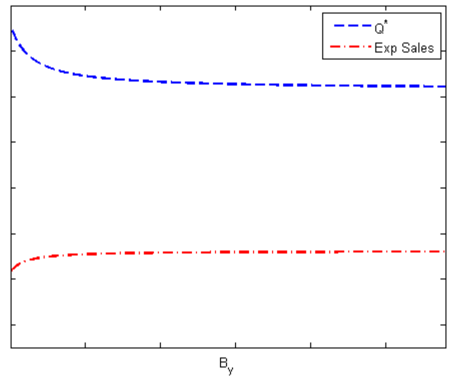


Figure 6.1: Example for Remark 5

We discuss the effect of the budget size in subsection 6.3.2.4. In the remaining part of the study, we continue our analysis by taking the objective as expected sales.

Expected sales with respect to our demand and yield models can be expressed as follows (by Theorem 2.1 in [67]) :

$$\begin{aligned} E[min\{YQ,D\}] = \quad & H_D(B_d)\Phi\left(\frac{ln(Q)-ln(H_D(B_d))-\sigma_D^2/2+ln(H_Y(B_y))-\sigma_Y^2/2+\rho\sigma_D\sigma_Y}{\sqrt{\sigma_D^2+\sigma_Y^2-2\rho\sigma_D\sigma_Y}}\right) \\ + \quad & H_Y(B_y)Q\Phi\left(\frac{-ln(Q)+ln(H_D(B_d))-\sigma_D^2/2-ln(H_Y(B_y))-\sigma_Y^2/2+\rho\sigma_D\sigma_Y}{\sqrt{\sigma_D^2+\sigma_Y^2-2\rho\sigma_D\sigma_Y}}\right) \end{aligned} \tag{6.14}$$

6.2.4.1 Reformulation

In this part, using expected sales as the objective function and utilizing the optimal solution characteristics of the problem for a concave utility function of Q (i.e. Proposition 6.1 and Equation (6.7), we express the problem in terms of a single variable.

$$
\begin{aligned}
\max_{B_y} \quad & H_D(B-B_y)\Phi\left(\Phi^{-1}\left(\frac{pH_Y(B_y)-c}{(p-s)H_Y(B_y)}\right)-\sqrt{\sigma_D^2+\sigma_Y^2-2\rho\sigma_D\sigma_Y}\right)+H_Y(B_y)\left(\frac{c-sH_Y(B_y)}{(p-s)H_Y(B_y)}\right)\times \\
& e^{[\Phi^{-1}(\frac{pH_Y(B_y)-c}{(p-s)H_Y(B_y)})\sqrt{\sigma_Y^2+\sigma_D^2-2\rho\sigma_Y\sigma_D}-\ln(H_Y(B_y))+\ln(H_D(B-B_y))-\sigma_Y^2/2-\sigma_D^2/2+\rho\sigma_Y\sigma_D]} \qquad (6.15) \\
\text{s.t.} \quad & 0 \le B_y \le B \qquad (6.16)
\end{aligned}
$$

We conduct a set of numerical experiments to study the structure of the problem for the following mean demand and yield functions; $H_D(B-B_y)=\mu+\mu w(B-B_y)^{\alpha}$ and $H_Y(B_y)=\frac{kB_y+1}{kB_y+a}$. In the examples solved, we observe that the objective function is concave with respect to B_y.

6.2.4.2 What if we use only $E[Y]$ in the expected sales expression?

In this subsection, we define a new objective function that is $E[min\{E[Y]Q,D\}]$, which is alike expected sales, and compare its value with the former one for given intervention design. Specifically, we replace $E[min\{YQ,D\}]$ term with $E[min\{E[Y]Q,D\}]$. We consider this situation as one would see such cases in practice. The new objective function for bivariate lognormal distribution can be written down as follows:

$$
\begin{aligned}
E[min\{E[Y]Q,D\}] = \quad & H_D(B_d)\Phi\left(\frac{ln(E[Y]Q)-ln(H_D(B_d))-\sigma_D^2/2}{\sigma_D}\right) \\
+ \quad & H_Y(B_y)Q\Phi\left(\frac{-ln(E[Y]Q)+ln(H_D(B_d))-\sigma_D^2/2}{\sigma_D}\right) \qquad (6.17)
\end{aligned}
$$

Proposition 6.2 *Given B_d and B_y, the following relations hold between the two objective function candidates:*

$$
\begin{aligned}
&\textit{If } \rho \le 0, && E[min\{E[Y]Q,D\}] > E[min\{YQ,D\}] \qquad , \\
&\textit{Otherwise}, && E[min\{E[Y]Q,D\}] = E[min\{YQ,D\}] \ \textit{ if } \ \sigma_Y = 2\rho\sigma_D \\
& && E[min\{E[Y]Q,D\}] > E[min\{YQ,D\}] \ \textit{ if } \ \sigma_Y > 2\rho\sigma_D \\
& && E[min\{E[Y]Q,D\}] < E[min\{YQ,D\}] \ \textit{ if } \ \sigma_Y < 2\rho\sigma_D
\end{aligned}
$$

Proof: *See Appendix C.1.*

The conditions indicate that if demand and yield are uncorrelated or negatively correlated, $E[min\{E[Y]Q,D\}]$ overestimates the expected sales value. In general, the objective function value with $E[Y]$ replacing the random yield variable will either an over or under-estimate of the expected sales value.

6.3 Numerical analysis

In this section, we present a numerical study using demand and yield functions explained in Section 6.2.1 and decision model (SP) given in Section 6.2.3.2 with the objective of maximizing expected sales in order to gain insights about the impact of applying joint mechanism on US influenza vaccine market. The numerical study is conducted based on available information from prior studies on influenza vaccine supply chain and US influenza vaccine market. We investigate how the proposed intervention mechanism proceeds and provide a detailed discussion of the results. Before continuing with the numerical results, we first explain how we set up our parameter sets.

6.3.1 Data set and calibration procedure for demand model's parameters

We choose the cost parameters and yield information from prior related studies in the literature, the details can be found in Table 6.1. The remaining parameters to calibrate

Table 6.1: Base parameter set

Parameter	Value	Reference
p	\$15	[26]
c	\$3	[26]
s	\$0	[26]
a	1.43	[68]

are related to the demand and yield functions, namely k, cv_d, cv_y, ρ, μ, w, and α. Our available information allows us to calibrate only two of these variables given the others. With the limited available information, our approach is then to set some of these parameters to certain values and calibrate the remaining.

We think that the key parameters to calibrate are μ and α, both describing the shape of the demand function. So, we will set the remaining parameters, i.e. k, cv_d, cv_y, ρ, and w to a value and find μ and α, accordingly. Of course, our intention is to analyze the effect of varying these set parameter values on the results. Table 6.2 summarizes the range of values for these selected parameters.

Table 6.2: Parameter values used in numerical experiments

Parameter	**Value**
k	$\{10^{-5}, 10^{-6}, 10^{-7}\}$
w	0.05
$cv_D = cv_Y$	$\{0.5, 1, 2\}$
ρ	$\{-0.9, -0.5, 0, 0.5, 0.9\}$

Note that we use only one value for w, as we think that the calibration procedure will adjust the results obtained for the demand function. Additionally, relative values for k and w are important and hence varying only k will suffice. Note that k value is exogenously taken, since we do not have any information on the yield increasing strategies.

The available data used for calibration is explained below. CDC reports that 2009-2010 influenza season vaccination coverage among all persons aged higher than six months in the United States is 41.2%, which corresponds to 123.3 million people ([69]). Note that the population size under consideration is 299.272 million people. Besides, according to Department of Health and Human Resources' report CDC's fiscal year 2010 budget request for Influenza Program is $\$158,992,000$ ([70]).

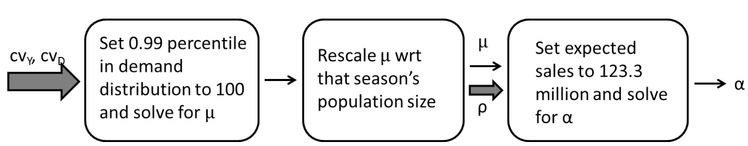


Figure 6.2: Steps utilized for calibrating parameters of the demand model

The steps of calibration used are briefly illustrated in Figure 6.2. Details of the procedure are presented in Appendix C.2. Calibrated μ and α values for varying values of coefficient of variation of demand, yield, and ρ are tabulated in Tables C.1 and C.2, respectively in Appendix C.2.

6.3.2 Analysis of results

In this section, we use the numerical results obtained as a basis to demonstrate the improvements that can be obtained by applying the proposed joint mechanism. Specifically, we investigate two main issues: (i) improvement in vaccination percentage, and (ii) budget savings with joint mechanism, both to get more complete information on the value of applying the joint mechanism. We further analyze two issues: the effect of considering yield uncertainty in this framework and the meaning of the total budget for the policy makers. The details of how computations are made are explained in Appendix C.2. Note that each numerical problem solved for a given budget level corresponds to a completely different problem environment due to change in demand model's parameter calibration process, so comparisons among problems may not be consistent. Of course, the problems where the only change is the total budget or k, the results are comparable.

6.3.2.1 Improvement in vaccination percentage

One of the reasonable measures to evaluate the performance of joint mechanism is vaccination percentage, which is the ratio of expected sales to population size under consideration. First, we analyze the vaccination percentage to be reached if joint mechanism is applied under that period's budget amount of 158.992 million. Table 6.3 reports the outcomes for varying values of k, coefficient variation of demand and yield, and ρ. The results demonstrate the importance of considering a joint mechanism that eliminates the inefficiencies emanating from both supply and demand sides. The numerical studies show that the vaccination rates of the 2009-2010 season is raised from 41.2% to a range between 42.46% and up to 58.28% depending on the values of k, cv_D, cv_Y, and ρ. The gap in the vaccinated percentage between the statistics of 2009-2010 season (41.2%) and the realized percentage under proposed strategy is quite high based on the fact that each percentage corresponds to approximately 2.9 million people. Also, we observe that the improvement in vaccination rates is greater for higher values of efficiency of yield improving strategy (k) as expected.

Besides, we compute and tabulate the vaccination rates for a representative set of budget values in Tables C.4 through C.6 in Appendix C.3. We observe that unless total budget is very tight, higher uncertainty in the system and negative correlation between demand and yield raise vaccination percentages even more with efficient allocation of budget among intervention alternatives [1].

Table 6.3: Vaccination percentages achieved by joint mechanism (%), as opposed to reported 41.2%

$cv_D = cv_Y$	k	ρ		
		-0.5	0	0.5
0.5	10^{-5}	44.99	44.06	42.99
	10^{-6}	44.69	43.84	42.86
	10^{-7}	43.79	43.18	42.46
1	10^{-5}	49.91	47.56	44.99
	10^{-6}	48.90	46.81	44.50
	10^{-7}	46.11	44.71	43.15
2	10^{-5}	58.28	53.46	48.28
	10^{-6}	56.18	51.93	47.32
	10^{-7}	50.55	47.79	44.76

6.3.2.2 Budget savings with joint mechanism

We further analyze the value of the joint mechanism proposed in terms of total budget spent. Specifically, we determine the budget required to achieve the aforementioned season's vaccination percentage with the joint mechanism, and demonstrate the savings in the required budget. In Table 6.4, we present percentage savings for varying values of k, cv_D, cv_Y, and ρ. The budget savings ranges between 28.01% and 89.81%.

[1]Note that cases with different ρ's and coefficient of variation values are not comparable, as the calibration procedure utilized yields different parameter values. We can see the effect of calibration under low budget values. However, the calibration procedure seems to work well under higher budgets. For instance, in the case where $cv_D = cv_Y = 0.5$ and budget is 30 million \$, the vaccination percentage first increases when ρ rises from -0.9 to -0.5 and then starts to decrease with more increase in the value of ρ. On the other hand, vaccination percentage decreases with ρ at higher budget values.

Clearly, applying joint mechanism substantially reduces the required budget to achieve the desired vaccination coverage, especially when uncertainty in the system is low. Also, the budget savings are reasonably high even the yield improving strategy's efficiency is tenfold lower. Based on the results depicted in Table 6.4, one can conclude that under higher uncertainty in the system, knowing the correlation would be very significant, of course, if it exists.

Table 6.4: Budget savings relative to current practice (%)

$cv_D = cv_Y$	k	ρ		
		-0.5	0	0.5
0.5	10^{-5}	87.90	89.10	89.81
	10^{-6}	82.45	83.84	84.71
	10^{-7}	65.47	67.28	68.55
1	10^{-5}	64.89	60.67	51.31
	10^{-6}	58.44	54.26	45.12
	10^{-7}	40.03	36.16	28.06
2	10^{-5}	65.82	61.29	51.37
	10^{-6}	59.36	54.86	45.14
	10^{-7}	40.90	36.67	28.01

6.3.2.3 What if yield is approximated by a deterministic function?

Although one can have estimates for the yield's mean and variance, it may as well be hard to fit a distribution. Thus, while solving these types of decision problems there is a tendency to represent yield by its average value, i.e. in our case this corresponds to a deterministic function of B_y. Here, we examine the influence of an imperfect yield without uncertainty on the vaccination percentage.

To obtain the optimal investment amounts (B_d^d and B_y^d) for deterministic yield case, we solve the decision model together with parameter calibration structure by setting yield's variance to zero. However, yield is uncertain in reality and this affects both the calibration and decision structures (See Table C.1 for μ values and C.3 for α values in Appendix C.2). Using the parameters reflecting yield variability, we evaluate Q and expected sales for B_d^d and B_y^d in order to observe the effect of considering deterministic yield. A representative set of results for equal values of cv_D and cv_Y, and $k = 10^{-6}$

are provided in Table 6.5, where optimal vaccination percentage found by taking into account yield's variability and realized percentage with deterministic yield are given in parentheses, respectively. Average loss in vaccination percentages is 0.05%, with the maximum being 0.12%. Comparing the two cases, one can observe that even if the central authority ignores yield uncertainty, it might end up with a vaccination rate in the ballpark of optimal solution by solving calibration and decision problems successively.

Table 6.5: Optimal vs realized vaccination percentages with deterministic yield $(\%, \%)$

ρ, cv	Budget ($\times 10^6$)							
	30	50	100	150	200	250	300	350
-0.9, 1	(35.01,34.96)	(39.18,39.12)	(45.61,45.56)	(49.85,49.80)	(53.10,53.05)	(55.77,55.73)	(58.06,58.01)	(60.06,60.02)
0, 1	(35.74,35.73)	(38.79,38.77)	(43.39,43.37)	(46.36,46.35)	(48.61,48.60)	(50.45,50.44)	(52.01,52.00)	(53.37,53.36)
0.9, 1	(36.19,36.14)	(37.88,37.84)	(40.39,40.36)	(41.99,41.96)	(43.18,43.16)	(44.15,44.12)	(44.96,44.94)	(45.67,45.65)
-0.9, 2	(31.04,30.94)	(38.06,37.96)	(49.83,49.72)	(58.16,58.04)	(64.82,64.70)	(70.46,70.35)	(75.42,75.30)	(79.85,79.74)
0, 2	(31.84,31.82)	(37.05,37.02)	(45.39,45.36)	(51.06,51.03)	(55.49,55.46)	(59.18,59.15)	(62.36,62.34)	(65.19,65.17)
0.9, 2	(32.39,32.29)	(35.24,35.16)	(39.63,39.56)	(42.52,42.45)	(44.71,44.65)	(46.51,46.46)	(48.05,47.99)	(49.39,49.34)

6.3.2.4 Which total budget is sufficient?

The effect of spending more is obviously going to result in more people being vaccinated. Given the structure of the objective function as well as the strategies considered, one may be interested in the effect of any additional budget on the outcome. Table 6.6 summarizes $ spent per additional person vaccinated using an additional budget of $\$10 \times 10^6$ (i.e. if total budget is $\$160 \times 10^6$, then we record $ spent per additional person vaccinated with the additional $\$10 \times 10^6$ budget used over $\$150 \times 10^6$) for different values of cv_D, cv_Y, ρ, and $k = 10^{-6}$.

Table 6.6: $ spent per additional person vaccinated with the additional budget of $\$10 \times 10^6$

cv_D, cv_Y	ρ	Total Budget ($\times 10^6$)				
		160	170	180	190	200
	-0.5	24.49	25.95	27.39	28.83	30.26
	0	34.45	36.54	38.61	40.68	42.73
0.5	0.5	57.47	61.03	64.58	68.12	71.64
	-0.5	5.43	5.70	5.98	6.24	6.51
	0	6.75	7.11	7.45	7.80	8.13
1	0.5	8.99	9.47	9.95	10.42	10.88
	-0.5	2.73	2.85	2.97	3.08	3.19
	0	3.47	3.63	3.79	3.94	4.10
2	0.5	4.76	4.99	5.22	5.45	5.67

Note that the results given above represent the additional budget spent to the cost of vaccine paid by the consumer. Comparing these numbers will be a good indication for the policy makers. At 150 million budget, the money spent per person ranges between \$0.86 and \$1.20 depending on cv_D, cv_Y, and ρ. However, we see that the additional budget spent per person can be considerably high for some cases due to concave structure of demand and yield models. For the cases where the budget spent per additional person vaccinated is higher than \$15, the policy maker may prefer to subsidize whole cost of vaccines instead of investing in demand and yield increasing strategies. Moreover, we can interpret whether the budget used in current practice is reasonable based on these results. If uncertainty in the system is high, the current budget used in practice seems to be reasonable and can be increased further; otherwise for low uncertainty case a much lower budget looks to be sufficient for investing in demand and yield increasing strategies.

6.4 Conclusion

Inspired from influenza vaccines, this chapter suggests a model to design intervention mechanism for a public-interest good facing yield issues in order to achieve socially desirable consumption/usage level. In particular, we consider a system composed of a manufacturer and a central planner that intervenes to the system through demand and yield increasing strategies. The goal of the intervention is to resolve the inefficiencies like insufficient demand and yield issues that are inherent to the system and motivate the channel to take socially more acceptable decisions. We develop and incorporate lognormal demand and yield models to our decision problem, general enough to be used in different contexts as well.

Strategies only targeting to improve demand may not be sufficient to reach optimal coverage levels in most of the cases, additional investments should be made to further improve the outcomes. This is also the case in US influenza vaccine market. Along with the numerical study, we show that the vaccination coverage in US can be increased considerably via the proposed joint mechanism by addressing both demand and yield issues in the system. Note that in addition to enhancing social welfare, proposed mechanism decreases total budget requirements for a desired level of vaccination.

Chapter 7

Conclusion

Wider adoption of health related goods, such as vaccines, or products with less carbon emissions have become a major focus of interest as social and environmental responsibility are becoming mainstream concerns. Within this focus, there is a need for a central authority implementing policies to promote usage of this type of goods. A key issue in this context is how to intervene in the supply chain of a such good so that its usage level is increased towards socially desirable levels. By intervention one can influence the demand of the good through demand-increasing strategies or supply for the good through subsidies, rebates or yield improving strategies. Here, main goal of the central authority is to allocate available budget among intervention alternatives so that the channel will react for the benefit of the system. This thesis provides guidelines to a central authority on designing intervention strategies to increase usage of public-interest goods. Specifically, we provided a unifying framework to produce strategies that will be influential in wider adoption of these goods in different settings with alternative intervention tools. We approached the problem as a budget allocation problem and especially explored the division of budget among intervention tools and their associated implications on the outcomes. We utilized bilevel programming for modeling this environment and after reducing the problems into single level mathematical programs, we solved them as non-linear programs.

The research conducted in this thesis can be categorized into three main groups in terms of intervention tools considered. Firstly, in Chapter 3 we were interested in intervention strategies including only subsidies in different settings. Central authority deals with registering subsidies under a budget constraint to improve supply of the public-interest good. Specifically, we first analyzed the problem for single echelon setting including single retailer and n retailers. For both cases, we derived upper limits on budget below which the central authority uses whole budget with the aim of maximizing utility. Following, we focused on a two echelon setting to analyze the problem for centralized and manufacturer driven systems. We present the modeling approach for the two systems. We noticed that the centralized system's formulation becomes identical with the single echelon model with single retailer. Regarding manufacturer driven system with uniformly distributed demand, we observed that the amount of subsidies only have influence over the profits of parties.

Next, motivated by the fact that current policies with rebates fail to reach targeted usage levels, we concentrated on joint intervention mechanisms that require two intervention tools to be applied simultaneously. Chapter 4 is devoted to analyzing a joint mechanism consisting of demand-increasing strategies and rebates. We formulated two social welfare maximization problems for a single echelon system with the aims of (i) optimizing budget and allocation among intervention tools and (ii) optimizing allocation of an exogenously determined budget among intervention tools. For both models, we characterized the structure of the optimal solution and showed that all budget will be used. For the model that optimizes budget and allocation among intervention tools, we found out that optimal rebate amount and investment made in demand-increasing strategies may be independent. Furthermore, we presented three benchmark approaches to assess the performance of proposed approaches. Finally, we used real-life data and information of California electric vehicle market in order to verify the proposed model and show benefits.

In Chapter 5 we considered a specific case of the model deciding on the optimal allocation of a given budget among intervention tools with exponentially distributed demand and constant demand effect. We found the optimal investment amounts to be made for each intervention tool and identified the optimal strategy in terms of budget level and efficiency of demand-increasing strategy. Our analysis on the optimal solution structure revealed that decisions made on intervention scheme without considering budget may result in significant budget deficits and excess money transfers to the retailer.

Lastly, we proposed a joint intervention mechanism composed of demand-increasing strategies and yield improving strategies for a public-interest good facing imperfect yield and yield uncertainty issues in Chapter 6. We analyzed the problem for a system composed of a manufacturer and a central authority with a certain budget amount. Demand and yield are assumed to follow bivariate lognormal distribution and expressed as functions of investments made to improve them. We characterized the optimal solution for specific forms of central authority's objective, and demand and yield functions. Finally, the models suggested are tested by a case study relying on the available estimates of US influenza market. The results imply that proposed strategy is very efficient in terms of vaccination percentages achieved and budget savings realized compared to the current practice, and the improvement in vaccination percentages is even greater when uncertainty in the system is higher.

One of the contributions of the thesis is to investigate a newsvendor environment with welfare implications using bilevel programming. We develop a modeling structure that is quite general and adaptable for alternative settings and intervention schemes. This opportunity enables the central authority to formulate different intervention schemes and examine the outcomes of each scheme. We find out structural results that will ease the procedure to find the optimal solution and also provide insights to central authority while generating policies. Besides, exploring an intervention mechanism consisting of investment in demand-increasing strategies as an additional intervention tool and considering an explicit budget constraint are new.

Further, we conduct two case studies based on real life data to analyze the benefits of proposed mechanisms by implementing novel parameter calibration approaches. Within case studies, we develop notions that play a supportive role in decisions to be made. One of the notions is the expected excess budget. We believe that with stochastic constraints, such quantities should be computed to reflect possible risks in the decisions made. One can evaluate the values of this risk measure while determining the applicability of the model's results. Another important proposal regards coordination.

We present the model that offers a coordination possibility for one of the models of Chapter 4. We elaborate the problem as a supply chain coordination problem, with the central authority being the firm with an integrated supply chain, and running demand-increasing strategies and incentivizing customer rebates. The model matches supply chain coordination topic, however it does not exactly suit public-interest good context. Using such a coordination scheme is more reasonable for a general newsvendor environment.

There are several directions for future research. First is to investigate the models in Chapter 3 with sales rebate and thus stochastic constraint. In the current studies we analyze joint intervention mechanisms with two intervention tools applied simultaneously. An extension would be to consider one more intervention tool. Note that another alternative for intervention tools can be investment which will decrease the manufacturing cost. Another future research direction would be to analyze models in Chapter 4 with a chance constraint instead of an expected value constraint. The constraint that we use in the models of Chapter 4 satisfies the budget limitation on rebate amounts in expectation as realized sales is stochastic. Thus, one can consider the case in which the probability of meeting the budget limitation on rebates is above a certain level when the central authority is risk-averse.

In this thesis, we address the intervention design problem in a single period setting. Analysis of the intervention mechanisms in a multi-period setting would be worthwhile as technology change and/or market adoption level are expected to affect the policy significantly. A reasonable approach is to model this problem as a two-stage stochastic program with demand learning. Then as the demand distribution is improved, the intervention scheme will be updated accordingly. Here, one would expect use of different intervention tools depending on the market conditions as in the single period setting case.

Another area of future work is to apply intervention design problem in different contexts. One example can be renewable energy investment problem. Renewable energy sources have received significant attention in the last decade due to increasing environmental concerns. However, volatility in energy prices and random yield issue inherent to renewable resources make this problem a challenging one. Recently, several incentive programs have been implemented in the US to encourage wider usage of renewable resources. Analysis of this problem together with a case study will generate key insights for policy makers who would like to make renewable resources more viable.

Bibliography

[1] G. Raz and A. Ovchinnikov, “Coordinating pricing and supply of public interest goods using government rebates and subsidies,” *Engineering Management, IEEE Transactions on*, vol. 62, no. 1, pp. 65–79, 2015.

[2] H. Mamani, E. Adida, and D. Dey, “Vaccine market coordination using subsidy,” *IIE Transactions on Healthcare Systems Engineering*, vol. 2, no. 1, pp. 78–96, 2012.

[3] R. Lobel and G. Perakis, “Consumer choice model for forecasting demand and designing incentives for solar technology.” Working Paper, Massachusetts Institute of Technology, Cambridge, MA, 2011.

[4] B. Colson, P. Marcotte, and G. Savard, “An overview of bilevel optimization,” *Annals of Operations Research*, vol. 153, no. 1, pp. 235–256, 2007.

[5] J. F. Bard, *Practical bilevel optimization: Algorithms and applications*. Kluwer Academic Publishers, 1998.

[6] J. Mereckiene, “Seasonal influenza vaccination in Europe overview of vaccination recommendations and coverage rates in the eu member states for the 201213 influenza season,” *European Centre for Disease Prevention and Control*, 2015.

[7] Centers for Disease Control and Prevention, “Flu vaccination coverage: United States, 2012-13 influenza season.” http://www.cdc.gov/flu/fluvaxview/coverage-1213estimates.htm, 2015.

[8] P. L. Joskow and N. L. Rose, “The effects of economic regulation,” *Handbook of Industrial Organization*, pp. 1449–1506, 1989.

[9] K. E. Train, *Optimal regulation: the economic theory of natural monopoly*. MIT Press Books, 1991.

[10] C. Jones, *Applied welfare economics*. Oxford, New York, 2005.

[11] D. Horsky and L. S. Simon, "Advertising and the diffusion of new products," *Marketing Science*, vol. 2, no. 1, pp. 1–17, 1983.

[12] S. Kalish and G. L. Lilien, "Optimal price subsidy policy for accelerating the diffusion of innovation," *Marketing Science*, vol. 2, no. 4, pp. 407–420, 1983.

[13] L. De Cesare and A. Di Liddo, "A stackelberg game of innovation diffusion: Pricing, advertising and subsidy strategies," *International Game Theory Review*, vol. 3, no. 04, pp. 325–339, 2001.

[14] R. B. Myerson, "Mechanism design," in *Allocation, Information and Markets*, pp. 191–206, Springer, 1989.

[15] M. O. Jackson, "Mechanism theory," *Available at SSRN 2542983*, 2014.

[16] M. Khouja, "The single-period (news-vendor) problem: literature review and suggestions for future research," *Omega*, vol. 27, no. 5, pp. 537–553, 1999.

[17] G. P. Cachon, "Supply chain coordination with contracts," *Handbooks in Operations Research and Management Science*, vol. 11, pp. 227–339, 2003.

[18] T. A. Taylor, "Supply chain coordination under channel rebates with sales effort effects," *Management Science*, vol. 48, no. 8, pp. 992–1007, 2002.

[19] X. Drèze and D. R. Bell, "Creating win–win trade promotions: Theory and empirical analysis of scan-back trade deals," *Marketing Science*, vol. 22, no. 1, pp. 16–39, 2003.

[20] G. Aydin and E. L. Porteus, "Manufacturer-to-retailer versus manufacturer-to-consumer rebates in a supply chain," in *Retail supply chain management*, pp. 237–270, Springer, 2008.

[21] S. E. Chick, H. Mamani, and D. Simchi-Levi, "Supply chain coordination and influenza vaccination," *Operations Research*, vol. 56, no. 6, pp. 1493–1506, 2008.

[22] S. Chick, S. Hasija, and J. Nasiry, "Incentive alignment and information elicitation from manufacturers for public goods procurement," 2012.

[23] H. Mamani, S. E. Chick, and D. Simchi-Levi, "A game-theoretic model of international influenza vaccination coordination," *Management Science*, vol. 59, no. 7, pp. 1650–1670, 2013.

[24] S. Deo and C. J. Corbett, "Cournot competition under yield uncertainty: The case of the US influenza vaccine market," *Manufacturing & Service Operations Management*, vol. 11, no. 4, pp. 563–576, 2009.

[25] E. Adida, D. Dey, and H. Mamani, "Operational issues and network effects in vaccine markets," *European Journal of Operational Research*, vol. 231, no. 2, pp. 414–427, 2013.

[26] K. Arifoğlu, S. Deo, and S. M. Iravani, "Consumption externality and yield uncertainty in the influenza vaccine supply chain: Interventions in demand and supply sides," *Management Science*, vol. 58, no. 6, pp. 1072–1091, 2012.

[27] T. A. Taylor and W. Xiao, "Subsidizing the distribution channel: Donor funding to improve the availability of malaria drugs," *Management Science*, vol. 60, no. 10, pp. 2461–2477, 2014.

[28] A. Atasu, Ö. Özdemir, and L. N. Van Wassenhove, "Stakeholder perspectives on e-waste take-back legislation," *Production and Operations Management*, vol. 22, no. 2, pp. 382–396, 2013.

[29] D. Krass, T. Nedorezov, and A. Ovchinnikov, "Environmental taxes and the choice of green technology," *Production and Operations Management*, vol. 22, no. 5, pp. 1035–1055, 2013.

[30] D. F. Drake, P. R. Kleindorfer, and L. N. Van Wassenhove, "Technology choice and capacity portfolios under emissions regulation," *Production and Operations Management*, 2015.

[31] M. C. Cohen, R. Lobel, and G. Perakis, "The impact of demand uncertainty on consumer subsidies for green technology adoption," *Management Science*, vol. 62, no. 5, pp. 1235–1258, 2016.

[32] J. Bracken and J. T. McGill, “Mathematical programs with optimization problems in the constraints,” *Operations Research*, vol. 21, no. 1, pp. 37–44, 1973.

[33] J. Bracken and J. T. McGill, “Defense applications of mathematical programs with optimization problems in the constraints,” *Operations Research*, vol. 22, no. 5, pp. 1086–1096, 1974.

[34] J. Bracken and J. McGill, “Production and marketing decisions with multiple objectives in a competitive environment,” *Journal of Optimization Theory and Applications*, vol. 24, no. 3, pp. 449–458, 1978.

[35] W. Candler and R. Norton, “Multilevel programming,” Tech. Rep. 20, World Bank Development Research Center, Washington D.C, 1977.

[36] L. N. Vicente and P. H. Calamai, “Bilevel and multilevel programming: A bibliography review,” *Journal of Global optimization*, vol. 5, no. 3, pp. 291–306, 1994.

[37] L. Brotcorne, P. Marcotte, and G. Savard, “Bilevel programming: The montreal school,” *INFOR: Information Systems and Operational Research*, vol. 46, no. 4, pp. 231–246, 2008.

[38] J.-P. Côté, P. Marcotte, and G. Savard, “A bilevel modelling approach to pricing and fare optimisation in the airline industry,” *Journal of Revenue and Pricing Management*, vol. 2, no. 1, pp. 23–36, 2003.

[39] D. W. Hearn and M. V. Ramana, “Solving congestion toll pricing models,” in *Equilibrium and advanced transportation modelling*, pp. 109–124, Springer, 1998.

[40] T. Larsson and M. Patriksson, “Side constrained traffic equilibrium modelsanalysis, computation and applications,” *Transportation Research Part B: Methodological*, vol. 33, no. 4, pp. 233–264, 1999.

[41] B. Y. Kara and V. Verter, “Designing a road network for hazardous materials transportation,” *Transportation Science*, vol. 38, no. 2, pp. 188–196, 2004.

[42] I. Constantin and M. Florian, "Optimizing frequencies in a transit network: a nonlinear bi-level programming approach," *International Transactions in Operational Research*, vol. 2, no. 2, pp. 149–164, 1995.

[43] J. F. Bard, J. Plummer, and J. Claude Sourie, "A bilevel programming approach to determining tax credits for biofuel production," *European Journal of Operational Research*, vol. 120, no. 1, pp. 30–46, 2000.

[44] M. Kočvara and J. V. Outrata, "Effective reformulations of the truss topology design problem," *Optimization and Engineering*, vol. 7, no. 2, pp. 201–219, 2006.

[45] A. Van Ackere, "The principal/agent paradigm: Its relevance to various functional fields," *European Journal of Operational Research*, vol. 70, no. 1, pp. 83–103, 1993.

[46] R. G. Jeroslow, "The polynomial hierarchy and a simple model for competitive analysis," *Mathematical programming*, vol. 32, no. 2, pp. 146–164, 1985.

[47] E. Z. Demirci and N. K. Erkip, "Designing an intervention strategy for public-interest goods: The california electric vehicle market case," *Omega*, 2016, forthcoming.

[48] M. Khouja and S. S. Robbins, "Linking advertising and quantity decisions in the single-period inventory model," *International Journal of Production Economics*, vol. 86, no. 2, pp. 93–105, 2003.

[49] C.-M. Lee and S.-L. Hsu, "The effect of advertising on the distribution-free newsboy problem," *International Journal of Production Economics*, vol. 129, no. 1, pp. 217–224, 2011.

[50] F. J. Arcelus, S. Kumar, and G. Srinivasan, "Pricing, rebate, advertising and ordering policies of a retailer facing price–dependent stochastic demand in newsvendor framework under different risk preferences," *International Transactions in Operational Research*, vol. 13, no. 3, pp. 209–227, 2006.

[51] S. X. Li, Z. Huang, J. Zhu, and P. Y. Chau, "Cooperative advertising, game theory and manufacturer–retailer supply chains," *Omega*, vol. 30, no. 5, pp. 347–357, 2002.

[52] California Environmental Protection Agency, "California, clean vehicle rebate project." `https://cleanvehiclerebate.org/eng`, 2014.

[53] WBCSD, *Mobility 2030: Meeting the challenges to sustainability*. World Business Council for Sustainable Development, 2004.

[54] U. Eberle and R. von Helmolt, "Sustainable transportation based on electric vehicle concepts: A brief overview," *Energy & Environmental Science*, vol. 3, no. 6, pp. 689–699, 2010.

[55] US Department of Energy, "One million electric vehicles by 2015, February 2011 status report." `http://www1.eere.energy.gov/vehiclesandfuels/pdfs/1_million_electric_vehicles_rpt.pdf`, Sept. 2011.

[56] Nissan Motor Corporation, "Nissan leaf global sales reach 100,000 units." `http://www.nissan-global.com/EN/NEWS/`, Sept. 2014.

[57] Nissan USA, "Nissan cars, trucks, crossovers, & suvs— nissan usa." `http://www.nissanusa.com`, Sept. 2013.

[58] True Car Inc. `http://www.truecar.com/prices-new/nissan/leaf-pricing/`, Sept. 2013.

[59] California Energy Commission, "California energy demand forecast 2012-2022 volume 1: Statewide electricity demand and methods, end-user natural gas demand, and energy efficiency," Tech. Rep. CEC2002012001SFVI, California Energy Commission, June 2012.

[60] W.-M. Lu, Q. L. Kweh, M. Nourani, and F.-W. Huang, "Evaluating the efficiency of dual-use technology development programs from the R&D and socio-economic perspectives," *Omega*, vol. 62, pp. 82–92, 2016.

[61] World Health Organization, "Influenza vaccines," *Weekly epidemiological record*, vol. 80, no. 33, pp. 277–287, 2005.

[62] Centers for Disease Control and Prevention, "How influenza (flu) vaccines are made." http://www.cdc.gov/flu/protect/vaccine/how-fluvaccine-made.htm, 2015.

[63] National Vaccine Advisory Committee, "Strengthening the supply of routinely recommended vaccines in the United States." http://www.hhs.gov/nvpo/nvac/nvac-vsr.html, 2003.

[64] The New York Times, "Good talks needed to combat HPV vaccine myth." http://www.nytimes.com/2015/11/10/upshot/hpv-vaccine-myth-good-talks-needed.html?emc=eta1&_r=0, 2015.

[65] World Health Organization, "Global action plan for influenza vaccines." http://www.who.int/influenza_vaccines_plan/objectives/en/, 2015.

[66] C. A. Yano and H. L. Lee, "Lot sizing with random yields: A review," *Operations Research*, vol. 43, no. 2, pp. 311–334, 1995.

[67] D. Lien and N. Balakrishnan, "Moments and properties of multiplicatively constrained bivariate lognormal distribution with applications to futures hedging," *Journal of Statistical Planning and Inference*, vol. 136, no. 4, pp. 1349–1359, 2006.

[68] S.-H. Cho, "The optimal composition of influenza vaccines subject to random production yields," *Manufacturing & Service Operations Management*, vol. 12, no. 2, pp. 256–277, 2010.

[69] Centers for Disease Control and Prevention, "Influenza (flu): 2009-10 flu season." http://www.cdc.gov/flu/fluvaxview/coverage_0910estimates.htm, 2015.

[70] Centers for Disease Control and Prevention, "Influenza (flu): 2009-10 flu season." http://www.cdc.gov/budget/documents/fy-2010congressional-justification.pdf, 2015.

Appendix A

Intervention by Incentives

A.1 Proofs

Proof of Proposition 3.1:

a)If $r = c - p$, then $Q^* = 0$ from the definition of cdf of demand. Note that this case can only arise when $B = 0$.

If $r = c - s$, $Q^* = D_{max}$ following the assumption on cdf of demand. In this case, the budget constraint will be active when $B = (c - s)D_{max}$ and will not be binding otherwise.

b)When $0 \leq B \leq (c - s)D_{max}$, the budget constraint will be always binding. The reason behind this is that utility is an increasing concave function of Q, which is also an increasing function of r. For this instance, $\frac{\partial z(r)}{\partial r} = \lambda_1 \frac{\partial g(r)}{\partial r}$ will be satisfied by the optimal solution following the KKT conditions.

Proof of Proposition 3.2:

The proof is similar to that of Proposition 3.1 part b.

Proof of Proposition 3.3:

Suppose for a contradiction that there exists some solution $(\overline{\mathbf{r}}, \overline{\mathbf{Q}})$ such that $(\overline{\mathbf{r}}, \overline{\mathbf{Q}})$ is different than $(\mathbf{r}^*, \mathbf{Q}^*)$ and $(\overline{\mathbf{r}}, \overline{\mathbf{Q}})$ has a larger total utility. This implies that $\overline{\mathbf{r}}$ and $\mathbf{r}^*$, and so $\overline{\mathbf{Q}}$ and $\mathbf{Q}^*$ should differ at least in two coordinates. Therefore, $\exists i$ and $j \in 1, \cdots, n$ such that $\overline{r}_i < \overline{r}_j$ and consequently $\overline{Q}_i \leq \overline{Q}_j$. If we decrease $\overline{r}_j$ by ε and increase $\overline{r}_i$ by ε, we will arrive at a solution $(\widetilde{\mathbf{r}}, \widetilde{\mathbf{Q}})$ for which $\widetilde{Q}_i > \overline{Q}_i$ and $\widetilde{Q}_j < \overline{Q}_j$. Assume that ε is large enough so that $(\widetilde{\mathbf{r}}, \widetilde{\mathbf{Q}}) \neq (\overline{\mathbf{r}}, \overline{\mathbf{Q}})$. The decrease in the utility of agent j will be less than the increase in the utility of agent i, hence the total value of $(\widetilde{\mathbf{r}}, \widetilde{\mathbf{Q}})$ is greater than $(\overline{\mathbf{r}}, \overline{\mathbf{Q}})$'s. Hence this contradicts with the optimality of $(\overline{\mathbf{r}}, \overline{\mathbf{Q}})$.
Continuing in this manner, i.e. by increasing and decreasing r values, we will reach at $(\mathbf{r}^*, \mathbf{Q}^*)$.

Proof of Lemma 3.1:

It follows from Proposition 3.2 and Proposition 3.3.

Proof of Proposition 3.4:

Suppose for a contradiction that there exists a solution different than $(\mathbf{r}^*, \mathbf{Q}^*)$, say $(\overline{\mathbf{r}}, \overline{\mathbf{Q}})$ such that given solution structure does not hold. Then, there exists $i, j \in 1, \cdots, n$ such that $i < j$ and $\overline{r}_i > \overline{r}_j$ and $\overline{Q}_i > \overline{Q}_j$. But if we decrease $\overline{r}_i$ and increase $\overline{r}_j$ by the same amount, we will arrive at a solution with larger total value since marginal utility of agent j is greater than marginal utility of agent i. Hence, this contradicts with the optimality of $(\overline{\mathbf{r}}, \overline{\mathbf{Q}})$.

Proof of Lemma 3.2:

If demand is uniformly distributed over interval $[a, b]$, then the newsvendor optimal order quantity can be expressed as $Q = \frac{(p+r_r-c)(b-a)}{p-s} + a$. In that case, $\mathbb{E}[P_m(c)]$ is concave with respect to c. Also, note that the constraints of the follower's problem are linear. Thus, instead of analyzing *Model MD-BLP* directly, we can address an alternative formulation by replacing lower level problem by its KKT conditions (by pg. 312 of [5]).

A.2 Numerical Studies for Two-Echelon Model

In this section, we provide a summary of the results obtained from the computational studies and list the observations in the main text. The aim of these studies is to explore how central authority registers subsidies to each party under different parameter settings. We solve *Model C-SLP* and *Model MD-SLP* by nonlinear solver CONOPT within GAMS environment. Note that we can not guarantee that the solutions obtained are optimal.

Throughout the numerical studies, we assume that demand is uniformly distributed on [0,1000], $p = 25$, $m = 15$, $s = 3$ unless otherwise stated.

Table A.1: Results when $p = 25$, $m = 15$, $s = 3$

	Centralized Pr.		Manuf.-Driven Pr.	
Budget	Exp. Sales	Q	Exp. Sales	Q
0	351.24	454.55	201.45	227.27
1000	393.69	538.89	256.69	302.42
1250	401.71	556.62	266.70	316.92
1500	409.03	573.44	275.85	330.44
1750	415.74	589.49	284.29	343.17
2000	421.93	604.85	292.14	355.23
2250	427.65	619.61	299.48	366.72
2500	432.96	633.83	306.37	377.70
2750	437.90	647.57	312.88	388.25
3000	442.50	660.88	319.04	398.41
3250	446.79	673.79	324.90	408.22

Table A.2: Results when $p = 25$, $m = 20$, $s = 3$

	Centralized Pr.		Manuf.-Driven Pr.	
Budget	Exp. Sales	Q	Exp. Sales	Q
0	201.45	227.27	107.18	113.64
1000	292.14	355.23	194.18	217.93
1250	306.37	377.70	207.15	234.69
1500	319.04	398.41	218.75	250.00
1750	330.47	417.71	229.29	264.19
2000	340.87	435.85	238.97	277.46
2250	350.41	453.03	247.94	289.98
2500	359.22	469.37	256.30	301.86
2750	367.39	485.00	264.15	313.19
3000	375.00	500.00	271.54	324.04
3250	382.11	514.44	278.54	334.47

Table A.3: Results when $p = 25$, $m = 23$, $s = 3$

	Centralized Pr.		Manuf.-Driven Pr.	
Budget	Exp. Sales	Q	Exp. Sales	Q
0	86.78	90.91	44.42	45.45
1000	228.74	263.45	159.84	175.19
1250	246.61	288.12	174.22	192.80
1500	262.29	310.50	186.97	208.76
1750	276.31	331.13	198.48	223.45
2000	288.99	350.37	209.02	237.14
2250	300.58	368.47	218.75	250.00
2500	311.26	385.61	227.81	262.17
2750	321.15	401.92	236.29	273.76
3000	330.36	417.52	244.27	284.83
3250	338.96	432.49	251.81	295.45

Table A.4: Results when $p = 25$, $m = 15$, $s = 10$

	Centralized Pr.		Manuf.-Driven Pr.	
Budget	Exp. Sales	Q	Exp. Sales	Q
0	444.44	666.67	277.78	333.33
1000	469.98	754.97	328.23	413.87
1250	474.53	774.29	337.66	430.19
1500	478.53	792.80	346.29	445.55
1750	482.06	810.59	354.26	460.11
2000	485.16	827.75	361.65	473.98
2250	487.88	844.32	368.55	487.26
2500	490.25	860.38	375.00	500.00
2750	492.31	875.96	381.06	512.27
3000	494.07	891.11	386.77	524.13
3250	495.57	905.85	392.17	535.60

Table A.5: Results when $p = 25$, $m = 23$, $s = 10$

	Centralized Pr.		Manuf.-Driven Pr.	
Budget	Exp. Sales	Q	Exp. Sales	Q
0	124.44	133.33	64.44	66.67
1000	277.78	333.33	194.96	218.93
1250	297.08	362.94	211.32	240.16
1500	313.86	389.85	225.76	259.41
1750	328.70	414.68	238.74	277.15
2000	341.99	437.85	250.55	293.67
2250	354.02	459.66	261.41	309.22
2500	364.97	480.32	271.46	323.93
2750	375.00	500.00	280.83	337.93
3000	384.23	518.82	289.60	351.31
3250	392.77	536.89	297.85	364.16

Appendix B

Joint Mechanism Composed of Demand-increasing Strategies and Rebates

B.1 Proofs

Proof of Corollary 4.1:

Considering (4.16), $Q = F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right)$ and $1 - F_{B_d}(Q) = \left(\frac{c-s}{p+r-s}\right)$. Hence, we can express expected sales as:

$$\mathbb{E}[min\{Q,D\}|B_d] = \int_0^{F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right)} x f_{B_d}(x)dx + \left(\frac{c-s}{p+r-s}\right) F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right) \quad \text{(B.1)}$$

Using B.1 for the expected sales, the objective function can be written as:

$$u(B_d, r) = (\beta - r)\left\{\int_0^{F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right)} x f_{B_d}(x)dx + \left(\frac{c-s}{p+r-s}\right) F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right)\right\} - B_d \quad \text{(B.2)}$$

Next, we consider first order condition of (B.2) with respect to r, which is given below:

$$\int_0^{F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right)} x f_{B_d}(x)dx + \left(\frac{c-s}{p+r-s}\right) F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right)$$
$$= (\beta - r)\frac{1}{f_{B_d}\left(F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right)\right)}\frac{(c-s)^2}{(p+r-s)^3} \tag{B.3}$$

After evaluating (B.3) for exponential and lognormal distribution and rearranging, it can be shown that optimal rebate is independent of $\mu(B_d)$ for the mentioned distributions.

(i) Assume that demand is exponentially distributed with mean $\mu(B_d)$. Then, (B.3) can be written as:

$$\mu(B_d)\left(\frac{c-s}{p+r-s}\right) ln\left(\frac{c-s}{p+r-s}\right) + \mu(B_d)\left(\frac{p+r-c}{p+r-s}\right)$$
$$-\mu(B_d)\left(\frac{c-s}{p+r-s}\right) ln\left(\frac{c-s}{p+r-s}\right) = (\beta - r)\mu(B_d)\frac{c-s}{(p+r-s)^2} \tag{B.4}$$

After rearranging (B.4), one can show that r can be found by $\sqrt{\beta(c-s)+c(p-s)-s(p-s)} - (p-s)$, which is independent of B_d and $\mu(B_d)$.

(ii) Assume that demand is lognormally distributed with parameters (v,τ) and mean $\mu(B_d)$. Note that $\mu(B_d) = e^{v+\tau^2/2}$. Given the optimal solution of the newsvendor problem, $F_{B_d}^{-1}\left(\frac{p+r-c}{p+r-s}\right) = e^{v+\tau z}$. Then, (B.3) can be expressed as follows:

$$e^{v+\tau^2/2}\Phi(z-\tau) + e^{v+\tau z}\left(\frac{c-s}{p+r-s}\right)$$
$$= (\beta - r)e^{v+\tau z}\tau\sqrt{2\pi}e^{-z^2/2}\frac{(c-s)^2}{(p+r-s)^3} \tag{B.5}$$

Using $\mu(B_d) = e^{v+\tau^2/2}$, one can show that (B.5) can be expressed independent of $\mu(B_d)$ and the result follows. □

Proof of Corollary 4.2:

This proof is similar to that of Corollary 4.1. Specifically, evaluating (B.3) with mean demand function given in (4.14) and coefficient of variation function (4.20), and rearranging give the result. Of course, in this case B_d cannot be eliminated in (B.3). $\square$

Proof of Proposition 4.3:

a) Suppose to the contrary that there exists some solution $(\overline{r},\overline{Q},B_d^*,B_r^*)$ such that $\overline{r} \neq r^*$, $\overline{Q} \neq Q^*$, $\overline{r}E[min\left\{\overline{Q},D\right\}|B_d = B_d^*] < B_r^*$, and it has a higher objective function value. Assume that we keep B_d^* and B_r^* constant and increase $\overline{r}$ by ε, then we will arrive at a solution $(\widehat{r},\widehat{Q},B_d^*,B_r^*)$, for which $\widehat{Q} > \overline{Q}$ by the monotonicity of F_{B_d}. Since the objective function is increasing concave with respect to Q, the new solution will give a higher objective value, which contradicts with optimality. Continuing in this manner, i.e. increasing r by small increments, we will reach (r^*,Q^*,B_d^*,B_r^*). The result then follows.

b) We follow the same logic as in part (a). Suppose for a contradiction that there exists some solution $(\overline{r},\overline{Q},\overline{B_d},\overline{B_r})$ such that $\overline{B_d}+\overline{B_r} < B$, and it has a higher objective function value. This implies that either $\overline{B_d} < B_d^*$ or $\overline{B_r} < B_r^*$, or both.

When $\overline{B_d} < B_d^*$; if we increase $\overline{B_d}$ by ε, we will arrive at a solution $(\overline{r},\widehat{Q},\widehat{B_d},\overline{B_r})$ for which $\widehat{Q} > \overline{Q}$ by the first order stochastic dominance order of cdfs. Since the objective function is increasing with respect to Q and B_d, the new solution will result in a higher objective function value, which contradicts with optimality.

When $\overline{B_r} < B_r^*$; if we increase $\overline{B_r}$ by ε, $\overline{r}$ and $\overline{Q}$ also increase by part (a). Now, we arrive at a new solution $(\widetilde{r},\widetilde{Q},\overline{B_d},\widetilde{B}_r)$, for which $\widetilde{r} > \overline{r}$ and thus $\widetilde{Q} > \overline{Q}$ by the monotonicity of cdf. $\widetilde{Q}$ has a higher objective function value, which contradicts with optimality.

Last, if both $\overline{B_d} < B_d^*$ and $\overline{B_r} < B_r^*$, we can arrive at a better solution by playing with B_d and B_r values in the same manner as in the previous cases, and this contradicts with the optimality of $(\overline{r},\overline{Q},\overline{B_d},\overline{B_r})$. In each of the three cases, by continuing to increase the values of B_d or/and B_r, we can achieve the optimal solution (r^*,Q^*,B_d^*,B_r^*). The result then follows. □

B.2 Demand Model's Parameters for Medium- and Long-Term Scenarios and Calibrated β Values

Table B.1: Demand model's parameters (μ_∞, d) for medium-term scenario

	s=$23,040		s=$18,720	
cv	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		(1,081,703, 789,863)		(1,081,703, 696,060)
1	(1,081,703, 544,766)	(1,081,703, 720,692)	(1,081,703, 87,552)	(1,081,703, 581,632)
1.2		(1,081,703, 643,120)		(1,081,703, 449,001)

Table B.2: Demand model's parameters (μ_∞, d) for long-term scenario

	s=$23,040		s=$18,720	
cv	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		(3,574,670, 2,224,893)		(3,574,670, 1,960,669)
1	(3,574,670, 1,534,501)	(3,574,670, 2,030,053)	(3,574,670, 246,616)	(3,574,670, 1,638,347)
1.2		(3,574,670, 1,811,545)		(3,574,670, 1,264,751)

The numbers are presented with precision so that they can be used for performing explicit calculations for comparison if needed.

Table B.3: Calibrated β values

	s=$23,040		s=$18,720	
cv	Exp. Dist.	Logn. Dist.	Exp. Dist.	Logn. Dist.
0.8		3,132		3,802
1	4,058	3,582	3,788	4,487
1.2		4,012		5,161

B.3 Computational Results for Optimal Budget Case

We solve our models by the nonlinear solver CONOPT within the GAMS environment. We also perform runs with different nonlinear solvers included in GAMS environment, such as MINOS, BARON, KNITRO, etc. However, we attempt to solve our data instances with CONOPT because it produces more reliable results. The solutions are obtained very quickly, in approximately 0.004 seconds, because the problems are not very large.

Table B.4: Solutions of base-case scenario for cases 1 and 2

Case Nb.	β ($)	Mechanism	Objective ($\$ \times 10^6$)	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
1a	3200	JM	52.1	37.0	41.7	1,789	0.0	66.1	22.0	169.2
		JMFR	48.8	45.0	52.3	2,116	0.0	95.2	35.5	169.2
		FRA	48.8	45.0	52.3	2,116	0.0	95.2	35.5	169.2
1b	4150	JM	91.6	45.7	53.3	2,147	0.0	98.2	36.9	169.2
		JMFR	91.5	45.0	52.3	2,116	0.0	95.2	35.5	169.2
		FRA	91.5	45.0	52.3	2,116	0.0	95.2	35.5	169.2
1c	5100	JM	142.8	62.3	74.7	2,484	20.2	154.8	63.0	199.1
		JMFR	137.9	52.4	60.9	2,116	18.4	110.8	41.3	196.9
		FRA	134.3	45.0	52.3	2,116	0.0	95.2	35.5	169.2
2a	3200	JM	50.8	37.9	40.5	1,860	0.0	70.6	23.2	305.1
		JMFR	48.8	45.0	48.7	2,116	0.0	95.2	33.9	305.1
		FRA	48.8	45.0	48.7	2,116	0.0	95.2	33.9	305.1
2b	4150	JM	92.2	49.0	53.4	2,267	0.0	111.0	41.0	305.1
		JMFR	91.5	45.0	48.7	2,116	0.0	95.2	33.9	305.1
		FRA	91.5	45.0	48.7	2,116	0.0	95.2	33.9	305.1
2c	5100	JM	143.5	58.8	65.3	2,658	0.0	156.2	62.1	305.1
		JMFR	134.3	45.0	48.7	2,116	0.0	95.2	33.9	305.1
		FRA	134.3	45.0	48.7	2,116	0.0	95.2	33.9	305.1

Table B.5: Solutions of base-case scenario for case 3

Case Nb.	β ($)	Mechanism	Objective ($\$ \times 10^6$)	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
3a	3200	JM	72.9	54.2	56.3	1,324	28.7	71.7	26.2	154.6
		JMFR	50.6	58.6	64.0	2,116	13.0	124.1	62.9	127.1
		FRA	48.8	45.0	49.1	2,116	0.0	95.2	48.3	97.5
3b	4150	JM	134.5	74.6	78.7	1,569	58.0	117.0	49.6	190.5
		JMFR	120.9	85.3	93.0	2,116	52.5	180.4	91.4	184.8
		FRA	91.5	45.0	49.1	2,116	0.0	95.2	48.3	97.5
3c	5100	JM	213.2	90.4	96.8	1,806	84.5	163.2	76.0	212.7
		JMFR	208.4	97.7	106.5	2,116	83.0	206.6	104.7	211.7
		FRA	134.3	45.0	49.1	2,116	0.0	95.2	48.3	97.5
3d	3200	JM	62.1	40.3	42.4	1,413	9.9	57.0	21.1	139.3
		JMFR	48.8	45.0	49.6	2,116	0.0	95.2	46.0	118.1
		FRA	48.8	45.0	49.6	2,116	0.0	95.2	46.0	118.1
3e	4150	JM	109.9	59.4	63.7	1,689	36.3	100.3	42.7	180.0
		JMFR	103.3	67.1	74.1	2,116	33.3	142.0	68.7	176.2
		FRA	91.5	45.0	49.6	2,116	0.0	95.2	46.0	118.1
3f	5100	JM	173.7	74.4	81.3	1,956	60.3	145.6	67.7	204.9
		JMFR	172.7	78.0	86.0	2,116	59.9	165.0	79.7	204.6
		FRA	134.3	45.0	49.6	2,116	0.0	95.2	46.0	118.1
3g	3200	JM	58.9	34.3	36.4	1,483	0.0	50.9	19.0	141.2
		JMFR	48.8	45.0	50.1	2,116	0.0	95.2	44.2	141.2
		FRA	48.8	45.0	50.1	2,116	0.0	95.2	44.2	141.2
3h	4150	JM	97.5	48.6	52.9	1,785	17.6	86.8	36.8	172.4
		JMFR	94.2	54.2	60.3	2,116	15.9	114.6	53.2	169.9
		FRA	91.5	45.0	50.1	2,116	0.0	95.2	44.2	141.2
3i	5100	JM	150.6	62.8	69.7	2,077	39.2	130.4	60.0	199.5
		JMFR	150.6	63.6	70.8	2,116	39.2	134.5	62.5	199.5
		FRA	134.3	45.0	50.1	2,116	0.0	95.2	44.2	141.2

Table B.6: Solutions of base-case scenario for case 4

Case Nb.	β ($)	Mechanism	Objective ($\$ \times 10^6$)	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
4a	3200	JM	65.2	38.4	39.1	1,299	7.8	49.9	18.1	142.0
		JMFR	48.8	45.0	46.9	2,116	0.0	95.2	48.7	125.5
		FRA	48.8	45.0	46.9	2,116	0.0	95.2	48.7	125.5
4b	4150	JM	109.6	54.5	55.8	1,549	32.1	84.4	35.9	180.0
		JMFR	99.5	62.4	65.0	2,116	27.4	132.0	67.4	173.8
		FRA	91.5	45.0	46.9	2,116	0.0	95.2	48.7	125.5
4c	5100	JM	167.6	67.1	69.3	1,799	54.0	120.8	56.8	203.8
		JMFR	164.1	72.7	75.8	2,116	52.9	153.9	78.6	202.7
		FRA	134.3	45.0	46.9	2,116	0.0	95.2	48.7	125.5
4d	3200	JM	61.4	33.9	34.7	1,388	0.0	47.0	17.5	159.5
		JMFR	48.8	45.0	47.2	2,116	0.0	95.2	46.5	159.5
		FRA	48.8	45.0	47.2	2,116	0.0	95.2	46.5	159.5
4e	4150	JM	96.5	41.6	43.0	1,672	6.7	69.6	29.9	171.4
		JMFR	91.7	47.2	49.5	2,116	4.3	99.9	48.8	167.3
		FRA	91.5	45.0	47.2	2,116	0.0	95.2	46.5	159.5
4f	5100	JM	141.7	53.1	55.4	1,955	25.4	103.9	48.9	197.7
		JMFR	141.0	55.7	58.4	2,116	25.2	117.8	57.5	197.4
		FRA	134.3	45.0	47.2	2,116	0.0	95.2	46.5	159.5
4g	3200	JM	59.2	34.0	35.0	1,459	0.0	49.6	18.6	199.0
		JMFR	48.8	45.0	47.4	2,116	0.0	95.2	44.8	199.0
		FRA	48.8	45.0	47.4	2,116	0.0	95.2	44.8	199.0
4h	4150	JM	94.3	39.6	41.2	1,770	0.0	70.1	30.1	199.0
		JMFR	91.5	45.0	47.4	2,116	0.0	95.2	44.8	199.0
		FRA	91.5	45.0	47.4	2,116	0.0	95.2	44.8	199.0
4i	5100	JM	134.3	44.5	46.8	2,080	0.0	92.5	43.2	199.0
		JMFR	134.3	45.0	47.4	2,116	0.0	95.2	44.8	199.0
		FRA	134.3	45.0	47.4	2,116	0.0	95.2	44.8	199.0

Table B.7: Solutions of medium-term scenario for cases 5 and 6

Case Nb.	β ($)	Mechanism	Objective ($\$ \times 10^6$)	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
5a	3200	JM	177.7	150.0	169.2	1,789	33.9	268.3	89.5	686.7
		JMFR	164.2	178.9	208.0	2,116	29.7	378.6	141.1	672.6
		FRA	154.8	142.8	166.0	2,116	0.0	302.2	112.6	536.9
5b	4150	JM	351.1	212.8	248.1	2,147	75.1	457.1	171.8	787.6
		JMFR	351.0	209.5	243.5	2,116	75.1	443.2	165.2	787.5
		FRA	290.5	142.8	166.0	2,116	0.0	302.2	112.6	536.9
5c	5100	JM	578.6	264.4	317.2	2,484	113.3	656.7	267.3	844.9
		JMFR	557.4	223.7	260.1	2,116	110.1	473.4	176.4	841.0
		FRA	426.2	142.8	166.0	2,116	0.0	302.2	112.6	536.9
6a	3200	JM	165.7	123.6	132.0	1,860	0.0	229.9	75.7	994.2
		JMFR	158.9	146.6	158.6	2,116	0.0	310.2	110.4	994.2
		FRA	158.9	146.6	158.6	2,116	0.0	310.2	110.4	994.2
6b	4150	JM	300.6	159.6	174.0	2,267	0.0	361.8	133.5	994.2
		JMFR	298.2	146.6	158.6	2,116	0.0	310.2	110.4	994.2
		FRA	298.2	146.6	158.6	2,116	0.0	310.2	110.4	994.2
6c	5100	JM	467.6	191.5	212.7	2,658	0.0	508.9	202.2	994.2
		JMFR	437.5	146.6	158.6	2,116	0.0	310.2	110.4	994.2
		FRA	437.5	146.6	158.6	2,116	0.0	310.2	110.4	994.2

Table B.8: Solutions of medium-term scenario for case 7

Case Nb.	β ($)	Mechanism	Objective ($\$\times10^6$)	Exp. Sales ($\times10^3$ vehicles)	Q ($\times10^3$ vehicles)	r ($)	B_d ($\$\times10^6$)	B_r ($\$\times10^6$)	EP[Q] ($\$\times10^6$)	$\mu(B_d)$ ($\times10^3$ vehicles)
7a	3200	JM	373.5	268.0	278.6	1,324	129.3	354.9	129.5	764.7
		JMFR	256.7	330.2	360.1	2,116	101.3	698.7	354.2	715.8
		FRA	145.9	134.6	146.8	2,116	0.0	284.9	144.4	291.8
7b	4150	JM	656.2	324.5	342.4	1,569	181.4	509.1	215.7	828.6
		JMFR	596.5	377.6	411.8	2,116	171.6	799.1	405.0	818.6
		FRA	273.8	134.6	146.8	2,116	0.0	284.9	144.4	291.8
7c	5100	JM	986.3	368.9	394.9	1,806	228.5	666.3	310.4	868.2
		JMFR	966.7	399.7	435.9	2,116	226.0	845.8	428.7	866.4
		FRA	401.8	134.6	146.8	2,116	0.0	284.9	144.4	291.8
7d	3200	JM	285.7	213.4	224.4	1,413	95.8	301.5	111.9	737.6
		JMFR	210.9	264.6	291.9	2,116	75.9	559.8	270.6	694.5
		FRA	149.1	137.5	151.7	2,116	0.0	291.0	140.7	361.0
7e	4150	JM	515.1	267.3	286.4	1,689	142.7	451.3	192.3	810.0
		JMFR	485.0	306.0	337.6	2,116	137.4	647.5	313.0	803.2
		FRA	279.7	137.5	151.7	2,116	0.0	291.0	140.7	361.0
7f	5100	JM	790.1	310.3	338.8	1,956	185.5	607.2	282.2	854.4
		JMFR	785.8	325.3	358.8	2,116	184.9	688.3	332.7	853.9
		FRA	410.4	137.5	151.7	2,116	0.0	291.0	140.7	361.0
7g	3200	JM	231.7	174.2	185.1	1,483	67.4	258.5	96.3	716.9
		JMFR	181.5	216.4	240.9	2,116	53.0	457.9	212.7	679.0
		FRA	151.5	139.8	155.6	2,116	0.0	295.8	137.4	438.6
7h	4150	JM	422.1	224.7	244.2	1,785	109.4	401.0	170.1	796.4
		JMFR	406.9	252.4	281.0	2,116	106.5	534.1	248.1	792.1
		FRA	284.3	139.8	155.6	2,116	0.0	295.8	137.4	438.6
7i	5100	JM	655.7	265.8	295.1	2,077	147.9	552.0	254.1	844.8
		JMFR	655.5	269.2	299.7	2,116	147.9	569.6	264.6	844.8
		FRA	417.1	139.8	155.6	2,116	0.0	295.8	137.4	438.6

Table B.9: Solutions of medium-term scenario for case 8

Case Nb.	β ($)	Mechanism	Objective ($\$\times10^6$)	Exp. Sales ($\times10^3$ vehicles)	Q ($\times10^3$ vehicles)	r ($)	B_d ($\$\times10^6$)	B_r ($\$\times10^6$)	EP[Q] ($\$\times10^6$)	$\mu(B_d)$ ($\times10^3$ vehicles)
8a	3200	JM	289.7	200.8	204.2	1,299	92.1	260.7	94.8	742.2
		JMFR	199.6	247.0	257.4	2,116	68.1	522.7	267.1	688.6
		FRA	150.0	138.3	144.2	2,116	0.0	292.7	149.6	385.6
8b	4150	JM	502.3	245.1	251.1	1,549	135.2	379.6	161.6	810.0
		JMFR	456.1	286.6	298.7	2,116	126.9	606.5	309.9	799.0
		FRA	281.4	138.3	144.2	2,116	0.0	292.7	149.6	385.6
8c	5100	JM	752.6	280.8	289.9	1,799	174.4	505.2	237.6	852.4
		JMFR	738.0	305.1	317.9	2,116	172.3	645.5	329.9	850.4
		FRA	412.8	138.3	144.2	2,116	0.0	292.7	149.6	385.6
8d	3200	JM	223.4	152.9	156.3	1,388	53.7	212.1	78.9	719.1
		JMFR	168.0	189.7	198.8	2,116	37.7	401.5	196.0	672.5
		FRA	152.9	141.1	147.9	2,116	0.0	298.5	145.8	500.1
8e	4150	JM	388.4	193.1	199.3	1,672	90.1	322.8	138.8	794.7
		JMFR	366.1	222.2	232.8	2,116	85.8	470.1	229.5	787.4
		FRA	287.0	141.1	147.9	2,116	0.0	298.5	145.8	500.1
8f	5100	JM	588.0	226.2	235.8	1,955	123.4	442.4	208.1	841.5
		JMFR	585.0	237.3	248.6	2,116	123.0	502.0	245.1	840.9
		FRA	421.0	141.1	147.9	2,116	0.0	298.5	145.8	500.1
8g	3200	JM	192.7	122.3	125.6	1,459	20.2	178.4	66.9	714.9
		JMFR	156.1	152.8	160.8	2,116	9.5	323.3	152.0	675.5
		FRA	155.1	143.1	150.6	2,116	0.0	302.8	142.3	632.7
8h	4150	JM	326.5	158.2	164.4	1,770	49.9	280.0	120.1	794.1
		JMFR	315.4	178.6	188.0	2,116	47.8	377.9	177.6	789.6
		FRA	291.1	143.1	150.6	2,116	0.0	302.8	142.3	632.7
8i	5100	JM	491.5	188.4	198.1	2,080	77.4	392.0	182.8	842.8
		JMFR	491.3	190.6	200.6	2,116	77.4	403.3	189.6	842.7
		FRA	427.0	143.1	150.6	2,116	0.0	302.8	142.3	632.7

Table B.10: Solutions of long-term scenario for cases 9 and 10

Case Nb.	β ($)	Mechanism	Objective ($\$ \times 10^6$)	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
		JM	783.2	639.6	721.6	1,789	119.3	1,144.1	381.6	2,927.8
9a	3200	JMFR	725.1	772.7	898.3	2,116	112.5	1,635.0	609.2	2,904.8
		FRA	588.3	542.7	630.9	2,116	0.0	1,148.3	427.9	2,040.2
		JM	1,487.3	835.9	974.5	2,147	186.7	1,795.0	674.7	3,093.0
9b	4150	JMFR	1,486.7	822.7	956.5	2,116	186.7	1,740.9	648.7	3,092.9
		FRA	1,103.8	542.7	630.9	2,116	0.0	1,148.3	427.9	2,040.2
		JM	2,360.4	997.4	1196.3	2,484	249.2	2,477.2	1,008.1	3,186.9
9c	5100	JMFR	2,280.4	846.0	983.6	2,116	244.1	1,790.2	667.1	3,180.6
		FRA	1,619.4	542.7	630.9	2,116	0.0	1,148.3	427.9	2,040.2
		JM	554.6	413.8	441.9	1,860	0.0	769.5	253.6	3,328.1
10a	3200	JMFR	532.1	490.8	531.0	2,116	0.0	1,038.6	369.6	3,328.1
		FRA	532.1	490.8	531.0	2,116	0.0	1,038.6	369.6	3,328.1
		JM	1,006.2	534.3	582.4	2,267	0.0	1,211.2	446.9	3,328.1
10b	4150	JMFR	998.4	490.8	531.0	2,116.0	0.0	1,038.6	369.6	3,328.1
		FRA	998.4	490.8	531.0	2,116	0.0	1,038.6	369.6	3,328.1
		JM	1,567.0	646.7	718.3	2,658	12.3	1,718.8	683.0	3,357.6
10c	5100	JMFR	1,465.5	494.1	534.5	2,116	8.8	1,045.4	372.0	3,349.9
		FRA	1,464.6	490.8	531.0	2,116	0.0	1,038.6	369.6	3,328.1

Table B.11: Solutions of long-term scenario for case 11

Case Nb.	β ($)	Mechanism	Objective ($\$ \times 10^6$)	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
		JM	1,733.9	1,071.1	1,113.1	1,324	275.5	1,418.0	517.4	3,055.6
11a	3200	JMFR	1,258.4	1,372.7	1,497.1	2,116	229.6	2,904.6	1,472.3	2,975.5
		FRA	675.0	622.7	679.1	2,116	0.0	1,317.6	667.9	1,349.8
		JM	2,833.9	1,237.6	1,306.0	1,569	360.8	1,941.5	822.7	3,160.3
11b	4150	JMFR	2,605.2	1,450.3	1,581.7	2,116	344.8	3,068.9	1,555.5	3,143.8
		FRA	1,266.6	622.7	679.1	2,116	0.0	1,317.6	667.9	1,349.8
		JM	4,074.7	1,370.1	1,467.0	1,806	438.0	2,475.0	1,152.8	3,225.1
11c	5100	JMFR	4,001.9	1,486.5	1,621.1	2,116	433.8	3,145.4	1,594.3	3,222.2
		FRA	1,858.1	622.7	679.1	2,116	0.0	1,317.6	667.9	1,349.8
		JM	1,336.8	871.3	916.0	1,413	220.6	1,230.8	456.8	3,011.1
11d	3200	JMFR	1,026.3	1,120.2	1,235.8	2,116	188.0	2,370.4	1,145.9	2,940.6
		FRA	637.9	588.4	649.1	2,116	0.0	1,245.1	601.9	1,544.6
		JM	2,244.2	1,032.7	1,106.8	1,689	297.5	1,743.9	743.0	3,129.7
11e	4150	JMFR	2,127.9	1,188.1	1,310.6	2,116	288.7	2,514.0	1,215.3	3,118.7
		FRA	1,196.9	588.4	649.1	2,116	0.0	1,245.1	601.9	1,544.6
		JM	3,289.2	1,163.3	1,269.7	1,956	367.5	2,275.9	1,057.8	3,202.5
11f	5100	JMFR	3,273.0	1,219.7	1,345.5	2,116	366.5	2,580.8	1,247.6	3,201.6
		FRA	1,755.9	588.4	649.1	2,116	0.0	1,245.1	601.9	1,544.6
		JM	1,068.1	723.6	768.5	1,483	174.2	1,073.4	399.9	2,977.3
11g	3200	JMFR	856.5	929.0	1,034.3	2,116	150.6	1,965.8	913.3	2,915.2
		FRA	609.1	561.9	625.5	2,116	0.0	1,188.9	552.4	1,763.1
		JM	1,830.9	876.8	952.7	1,785	242.9	1,564.8	663.8	3,107.6
11h	4150	JMFR	1,771.6	988.1	1,100.0	2,116	238.2	2,090.7	971.3	3,100.4
		FRA	1,142.9	561.9	625.5	2,116	0.0	1,188.9	552.4	1,763.1
		JM	2,725.4	1,002.6	1,113.0	2,077	305.9	2,082.1	958.7	3,186.7
11i	5100	JMFR	2,724.5	1,015.5	1,130.6	2,116	305.9	2,148.9	998.3	3,186.7
		FRA	1,676.7	561.9	625.5	2,116	0.0	1,188.9	552.4	1,763.1

Table B.12: Solutions of long-term scenario for case 12

Case Nb.	β ($)	Mechanism	Objective ($\$ \times 10^6$)	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
12a	3200	JM	1,338.1	816.6	830.4	1,299	214.5	1,060.4	385.5	3,018.8
		JMFR	964.4	1,051.4	1,095.7	2,116	175.3	2,224.7	1,136.9	2,931.0
		FRA	627.6	578.9	603.4	2,116	0.0	1,225.0	626.0	1,614.0
12b	4150	JM	2,178.1	946.9	970.2	1,549	285.1	1,466.5	624.4	3,129.8
		JMFR	1,998.9	1,116.2	1,163.3	2,116	271.5	2,361.9	1,207.0	3,111.8
		FRA	1,177.6	578.9	603.4	2,116	0.0	1,225.0	626.0	1,614.0
12c	5100	JM	3,130.0	1,054.0	1,088.1	1,799	349.3	1,896.3	891.7	3,199.1
		JMFR	3,075.0	1,146.4	1,194.8	2,116	345.9	2,425.8	1,239.7	3,196.0
		FRA	1,727.6	578.9	603.4	2,116	0.0	1,225.0	626.0	1,614.0
12d	3200	JM	996.8	633.6	647.8	1,388	151.6	879.2	327.1	2,980.9
		JMFR	762.9	819.5	858.8	2,116	125.4	1,734.0	846.7	2,904.6
		FRA	592.2	546.3	572.5	2,116	0.0	1,156.0	564.5	1,936.3
12e	4150	JM	1,658.0	754.2	778.6	1,672	211.2	1,260.9	542.1	3,104.7
		JMFR	1,570.6	872.6	914.5	2,116	204.2	1,846.4	901.6	3,092.8
		FRA	1,111.2	546.3	572.5	2,116	0.0	1,156.0	564.5	1,936.3
12f	5100	JM	2,423.7	855.3	891.5	1,955	265.8	1,672.5	786.6	3,181.3
		JMFR	2,412.5	897.3	940.4	2,116	265.1	1,898.7	927.1	3,180.4
		FRA	1,630.2	546.3	572.5	2,116	0.0	1,156.0	564.5	1,936.3
12g	3200	JM	788.9	508.7	522.6	1,459	96.8	742.1	278.2	2,974.0
		JMFR	634.0	658.1	692.7	2,116	79.4	1,392.5	654.5	2,909.6
		FRA	566.3	522.4	550.0	2,116	0.0	1,105.5	519.6	2,309.9
12h	4150	JM	1,325.7	618.2	642.5	1,770	145.5	1,094.3	469.6	3,103.8
		JMFR	1,282.4	700.3	737.2	2,116	142.0	1,481.9	696.5	3,096.4
		FRA	1,062.6	522.4	550.0	2,116	0.0	1,105.5	519.6	2,309.9
12i	5100	JM	1,958.4	711.7	748.2	2,080	190.5	1,480.6	690.6	3,183.4
		JMFR	1,957.9	720.0	757.9	2,116	190.5	1,523.5	716.1	3,183.4
		FRA	1,559.0	522.4	550.0	2,116	0.0	1,105.5	519.6	2,309.9

B.4 Computational Results for Exogenous Budget Case

Table B.13: Cases considered in the computational study

Case no.	**Distribution**	**cv**	**Horizon**	**s ($)**	**Budget ($ $\times 10^6$)**
13a, 13b, 13c	Exponential	1	Base Case	23,040	$\{76, 95, 114\}$
14a, 14b, 14c	Exponential	1	Base Case	18,720	$\{76, 95, 114\}$
15a-15i	Lognormal	$\{0.8, 1, 1.2\}$	Base Case	23,040	$\{76, 95, 114\}$
16a-16i	Lognormal	$\{0.8, 1, 1.2\}$	Base Case	18,720	$\{76, 95, 114\}$

Note that the letters in labels are assigned in the order of increasing values of budget first, then in increasing values of coefficient of variation.

Table B.14: Solutions of base-case scenario for cases 13 and 14

Case Nb.	Budget ($\$ \times 10^6$)	Mechanism	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
13a	76	JM2-SLP	39.9	45.5	1,904	0.0	76.0	26.5	169.2
		JM3-SLP	43.3	50.0	1,520	0.0	76.0	19.8	169.2
13b	95	JM2-SLP	44.9	52.2	2,114	0.0	95.0	35.4	169.2
		JM3-SLP	49.2	58.1	1,634	0.0	95.0	26.0	169.2
13c	114	JM2-SLP	49.4	58.0	2,228	3.9	110.1	42.3	175.9
		JM3-SLP	54.4	65.7	1,735	0.0	114.0	32.2	169.2
14a	76	JM2-SLP	39.6	42.4	1,919	0.0	76.0	25.5	305.1
		JM3-SLP	41.3	44.4	1,712	0.0	76.0	22.2	305.1
14b	95	JM2-SLP	44.9	48.6	2,114	0.0	95.0	33.8	305.1
		JM3-SLP	47.1	51.2	1,856	0.0	95.0	29.1	305.1
14c	114	JM2-SLP	49.7	54.2	2,294	0.0	114.0	42.3	305.1
		JM3-SLP	52.3	57.4	1,986	0.0	114.0	36.1	305.1

Table B.15: Solutions of base-case scenario for case 15

Case Nb.	Budget ($\$ \times 10^6$)	Mechanism	Exp. Sales ($\times 10^3$ vehicles)	Q ($\times 10^3$ vehicles)	r ($)	B_d ($\$ \times 10^6$)	B_r ($\$ \times 10^6$)	EP[Q] ($\$ \times 10^6$)	$\mu(B_d)$ ($\times 10^3$ vehicles)
15a	76	JM2-SLP	46.3	47.8	1,241	18.6	57.4	19.6	137.8
		JM3-SLP	49.6	52.1	1,239	14.5	61.5	20.8	130.1
15b	95	JM2-SLP	52.6	54.5	1,302	26.5	68.5	24.6	151.1
		JM3-SLP	56.7	59.9	1,299	21.4	73.6	26.2	142.6
15c	114	JM2-SLP	58.4	60.9	1,364	34.3	79.7	30.1	162.6
		JM3-SLP	63.4	67.4	1,358	27.9	86.1	32.1	153.3
15d	76	JM2-SLP	43.2	45.5	1,446	13.6	62.4	23.7	146.1
		JM3-SLP	47.6	51.6	1,429	8.0	68.0	25.4	135.5
15e	95	JM2-SLP	48.7	51.6	1,522	20.9	74.1	29.4	158.5
		JM3-SLP	54.1	59.2	1,498	14.0	81.0	31.5	146.9
15f	114	JM2-SLP	53.8	57.3	1,597	28.1	85.9	35.3	169.2
		JM3-SLP	60.2	66.5	1,565	19.7	94.3	38.0	156.6
15g	76	JM2-SLP	41.5	44.6	1,648	7.5	68.5	27.7	155.9
		JM3-SLP	47.1	52.8	1,603	0.5	75.5	29.8	142.2
15h	95	JM2-SLP	46.5	50.3	1,736	14.3	80.7	33.8	167.4
		JM3-SLP	53.2	60.4	1,678	5.8	89.2	36.4	152.6
15i	114	JM2-SLP	51.0	55.6	1,823	20.9	93.1	40.2	177.3
		JM3-SLP	59.0	67.8	1,751	10.7	103.3	43.4	161.5

Table B.16: Solutions of base-case scenario for case 16

Case Nb.	Budget ($\$\times10^6$)	Mechanism	Exp. Sales ($\times10^3$ vehicles)	Q ($\times10^3$ vehicles)	r ($)	B_d ($\$\times10^6$)	B_r ($\$\times10^6$)	EP[Q] ($\$\times10^6$)	$\mu(B_d)$ ($\times10^3$ vehicles)
16a	76	JM2-SLP	44.0	44.8	1,371	15.7	60.3	23.2	156.1
		JM3-SLP	45.6	46.6	1,375	13.3	62.7	24.1	152.1
16b	95	JM2-SLP	49.2	50.3	1,452	23.5	71.5	29.0	168.4
		JM3-SLP	51.2	52.5	1,456	20.5	74.5	30.1	163.9
16c	114	JM2-SLP	54.0	55.3	1,533	31.2	82.8	35.1	178.9
		JM3-SLP	56.3	58.0	1,536	27.5	86.5	36.6	174.0
16d	76	JM2-SLP	41.7	43.0	1,666	6.6	69.4	29.8	171.3
		JM3-SLP	43.9	45.6	1,660	3.2	72.8	31.1	165.3
16e	95	JM2-SLP	46.1	47.7	1,768	13.6	81.4	36.4	182.1
		JM3-SLP	48.7	50.9	1,759	9.3	85.7	37.9	175.6
16f	114	JM2-SLP	50.2	52.1	1,870	20.2	93.8	43.2	191.3
		JM3-SLP	53.3	56.0	1,856	15.1	98.9	45.1	184.3
16g	76	JM2-SLP	41.1	42.8	1,848	0.0	76.0	33.6	199.0
		JM3-SLP	43.8	45.9	1,737	0.0	76.0	32.2	199.0
16h	95	JM2-SLP	45.1	47.4	2,092	0.6	94.4	44.4	199.9
		JM3-SLP	48.5	51.5	1,957	0.0	95.0	43.0	199.0
16i	114	JM2-SLP	48.7	51.4	2,212	6.4	107.6	51.8	207.7
		JM3-SLP	52.8	56.7	2,160	0.0	114.0	54.0	199.0

Appendix C

Joint Intervention Mechanism In the Presence of Yield Uncertainty

C.1 Proofs and derivations

Analysis of lower level problem

We can rewrite the manufacturer's profit and expected profit functions as follows:

$$P(Q) = (p-s)min\{YQ, D\} - cQ + sYQ$$

$$E[P(Q)] = (p-s)E[min\{YQ, D\}] - cQ + sE[Y]Q$$

$E[min\{YQ, D\}]$ is given by

$$E[min\{YQ, D\}] = \int_0^\infty \left\{ \int_0^{YQ} x f_{D|Y}^{B_d}(x|y)dx + \int_{YQ}^\infty YQ f_{D|Y}^{B_d}(x|y)dx \right\} g^{B_y}(y)dy \quad \text{(C.1)}$$

Note that $f^{B_d}(.)$ and $g^{B_y}(.)$ are pdfs of demand and yield, respectively. The pdfs are dependent on the investment amounts allocated to improve demand and yield.

First derivative of expected sales is given by

$$\frac{\partial E[min\{YQ,D\}]}{\partial Q} = \int_0^\infty \int_{YQ}^\infty \left\{ f_{D|Y}^{B_d}(x|y)dx \right\} g^{B_y}(y)dy \tag{C.2}$$

$$= E[Y1_{\{D>YQ\}}] \tag{C.3}$$

Utilizing (C.3) one can write the first derivative of expected profit and equate it to zero, and derive the first order optimality condition as in (C.6).

$$\frac{\partial E[P(Q)]}{\partial Q} = (p-s)E[Y1_{\{D>YQ\}}] + sE[Y] - c \tag{C.4}$$

$$= pE[Y] - (p-s)E[Y1_{\{D\leq YQ\}}] - c \tag{C.5}$$

$$E[Y1_{\{D\leq YQ\}}] = \frac{pE[Y]-c}{p-s} \tag{C.6}$$

Proof of Proposition 6.1:

The result follows from the facts that $\frac{\partial Q}{\partial B_d} > 0$ and utility is an increasing concave function of Q. If $\frac{\partial Q}{\partial B_y} > 0$, then central authority will allocate all budget between B_d and B_y. Otherwise, whole budget will be assigned to B_d, leading to complete expenditure of the total budget.

Proof of Remark 6.5:

Differentiating (6.7) with respect to B_y, and using the fact that $H_Y(B_y)$ is increasing in B_y, we obtain the following:

$$\frac{\partial Q}{\partial B_y} = e^{[\Phi^{-1}(\frac{pH_Y(B_y)-c}{(p-s)H_Y(B_y)})\sqrt{\sigma_Y^2+\sigma_D^2-2\rho\sigma_Y\sigma_D}-\ln(H_Y(B_y))+\ln(H_D(B_d))-\sigma_Y^2/2-\sigma_D^2/2+\rho\sigma_Y\sigma_D]} \times \frac{H_Y(B_y)'}{H_Y(B_y)}\left(\frac{1}{\phi(\Phi^{-1}(\frac{pH_Y(B_y)-c}{(p-s)H_Y(B_y)})}\frac{c}{(p-s)H_Y(B_y)}\sqrt{\sigma_Y^2+\sigma_D^2-2\rho\sigma_Y\sigma_D}-1\right)$$

For deriving the condition that will make $\frac{\partial Q}{\partial B_y} > 0$, it suffices to find out when $\left(\frac{1}{\phi(\Phi^{-1}(\frac{pH_Y(B_y)-c}{(p-s)H_Y(B_y)})}\frac{c}{(p-s)H_Y(B_y)}\sqrt{\sigma_Y^2+\sigma_D^2-2\rho\sigma_Y\sigma_D}-1\right) > 0$.

Note that $H_Y(B_y)$ takes the value of at most 1 and $\phi(.)$ takes the value of at most 0.3989. Thus, when $\sqrt{\sigma_Y^2+\sigma_D^2-2\rho\sigma_Y\sigma_D} > 0.3989\left(\frac{p-s}{c}\right)$, the result follows.

Proof of Proposition 6.2:

Let $T = ln(H_Y(B_y)Q) - ln(H_D(B_d))$, then the functions can be expressed as follows:

$$E[min\{YQ,D\}] = H_D(B_d)\Phi\left(\frac{T-(\sigma_D-\sigma_Y)^2/2+(\rho-1)\sigma_D\sigma_Y}{\sqrt{(\sigma_D-\sigma_Y)^2+2(1-\rho)\sigma_D\sigma_Y}}\right) + H_Y(B_y)Q\Phi\left(\frac{-T-(\sigma_D-\sigma_Y)^2/2+(\rho-1)\sigma_D\sigma_Y}{\sqrt{(\sigma_D-\sigma_Y)^2+2(1-\rho)\sigma_D\sigma_Y}}\right) \tag{C.7}$$

$$E[min\{E[Y]Q,D\}] = H_D(B_d)\Phi\left(\frac{T-\sigma_D^2/2}{\sigma_D}\right)+H_Y(B_y)Q\Phi\left(\frac{-T-\sigma_D^2/2}{\sigma_D}\right) \tag{C.8}$$

Note that the following conditions always hold:

$$\sqrt{(\sigma_D-\sigma_Y)^2+2(1-\rho)\sigma_D\sigma_Y} > \sigma_D \text{ if } \sigma_Y > 2\rho\sigma_D \tag{C.9}$$

$$(\sigma_D-\sigma_Y)^2/2+(1-\rho)\sigma_D\sigma_Y > \sigma_D^2/2 \text{ if } \sigma_Y > 2\rho\sigma_D \tag{C.10}$$

Using the expressions (C.7) and (C.8), and conditions (C.9) and (C.10), we obtain the following relations between the functions:

$$E[min\{E[Y]Q,D\}] = E[min\{YQ,D\}] \text{ if } \sigma_Y = 2\rho\sigma_D \tag{C.11}$$

$$E[min\{E[Y]Q,D\}] > E[min\{YQ,D\}] \text{ if } \sigma_Y > 2\rho\sigma_D \tag{C.12}$$

$$E[min\{E[Y]Q,D\}] < E[min\{YQ,D\}] \text{ if } \sigma_Y < 2\rho\sigma_D \tag{C.13}$$

C.2 Details of the computations and calibration for the parameters of the demand model

Details of calibration for the parameters of the demand model:

The calibration method is briefly described in Figure 6.2. First two steps of the calibration are reiterated for each different pair of coefficient of variation of demand and yield, whereas last step is repeated for each coefficient of variation value of demand and yield, as well as ρ. Firstly, following the value of population size used in [26]'s numerical study, i.e. $N = 100$, we assume that 0.99 percentile in demand distribution corresponds to 100 vaccines, and obtain mean demand before investment, $H_D(B_d = 0)$ or μ. Then, we rescale μ along with the assumption that total population size of 299.272 million corresponds to 100 people. Lastly, we obtain α by setting expected sales to that aforementioned season's vaccination level. Note that last step is solved under the observation that all budget is invested in demand-increasing strategies.

Calibrated values for the parameters of the demand model:

Table C.1: Calibrated μ values

(cv_D, cv_Y)	$\mu(\times 10^3)$
(0.5,0.5)	111,497.6
(1,1)	61,014.7
(2,2)	34,980.2

Table C.2: Calibrated α values

$cv_D = cv_Y$	ρ				
	-0.9	-0.5	0	0.5	0.9
0.5	0.13	0.12	0.11	0.09	0.06
1	0.24	0.23	0.21	0.19	0.17
2	0.36	0.33	0.29	0.25	0.22

Table C.3: Calibrated α values when yield is assumed to be deterministic

cv_D	α
0.5	0.08
1	0.19
2	0.25

Details of the computations:

We solve model SP given in Section 6.2.3.2 by the nonlinear solver CONOPT within the GAMS environment. We also tested the model with different nonlinear solvers in GAMS environment that can solve logarithmic functions, like KNITRO. However, we observe that CONOPT produces more reliable results. The problems are solved very fast like within approximately 0.003 seconds. We also verify whether the solution obtained is optimal by enumerating the problem presented in Section 6.2.4.1.

C.3 Numerical results

Table C.4: Vaccination percentages when $cv_D = cv_Y = 0.5$ (%)

ρ	k	Budget ($ $\times 10^6$)							
		30	50	100	150	200	250	300	350
-0.9	10^{-5}	41.94	43.02	44.58	45.55	46.27	46.84	47.33	47.74
	10^{-6}	41.23	42.44	44.14	45.18	45.94	46.54	47.04	47.47
	10^{-7}	39.38	40.82	42.84	44.05	44.93	45.61	46.17	46.66
-0.5	10^{-5}	41.94	42.82	44.09	44.88	45.46	45.92	46.30	46.64
	10^{-6}	41.34	42.34	43.73	44.57	45.18	45.67	46.07	46.42
	10^{-7}	39.77	40.98	42.65	43.64	44.35	44.91	45.36	45.75
0	10^{-5}	41.86	42.50	43.41	43.97	44.38	44.71	44.98	45.21
	10^{-6}	41.42	42.15	43.15	43.75	44.19	44.53	44.81	45.06
	10^{-7}	40.23	41.13	42.36	43.07	43.58	43.98	44.30	44.58
0.5	10^{-5}	41.66	42.06	42.61	42.95	43.19	43.38	43.54	43.68
	10^{-6}	41.39	41.84	42.45	42.81	43.07	43.27	43.44	43.59
	$10−7$	40.64	41.20	41.96	42.40	42.70	42.94	43.13	43.30
0.9	10^{-5}	39.38	40.82	42.84	44.05	44.93	45.61	46.17	46.66
	10^{-6}	41.16	41.36	41.63	41.79	41.90	41.99	42.06	42.13
	10^{-7}	40.87	41.11	41.44	41.63	41.76	41.86	41.94	42.01

Table C.5: Vaccination percentages when $cv_D = cv_Y = 1$ (%)

ρ	k	Budget (\$ $\times 10^6$)							
		30	50	100	150	200	250	300	350
-0.9	10^{-5}	36.81	40.77	46.96	51.07	54.24	56.85	59.08	61.05
	10^{-6}	35.01	39.18	45.61	49.85	53.10	55.77	58.06	60.06
	10^{-7}	31.17	35.34	42.03	46.48	49.90	52.71	55.10	57.20
-0.5	10^{-5}	36.89	40.39	45.80	49.37	52.10	54.35	56.26	57.95
	10^{-6}	35.34	39.03	44.66	48.35	51.16	53.45	55.42	57.13
	10^{-7}	32.01	35.74	41.63	45.52	48.49	50.91	52.97	54.77
0	10^{-5}	36.96	39.84	44.25	47.13	49.32	51.11	52.64	53.97
	10^{-6}	35.74	38.79	43.39	46.36	48.61	50.45	52.01	53.37
	10^{-7}	33.15	36.25	41.09	44.24	46.62	48.55	50.20	51.63
0.5	10^{-5}	36.89	39.12	42.49	44.67	46.31	47.65	48.78	49.77
	10^{-6}	36.07	38.42	41.92	44.16	45.85	47.22	48.38	49.39
	10−7	34.39	36.77	40.43	42.80	44.58	46.01	47.23	48.28
0.9	10^{-5}	36.57	38.21	40.66	42.22	43.40	44.35	45.15	45.85
	10^{-6}	36.19	37.88	40.39	41.99	43.18	44.15	44.96	45.67
	10^{-7}	35.61	37.25	39.77	41.41	42.63	43.63	44.46	45.19

Table C.6: Vaccination percentages when $cv_D = cv_Y = 2$ (%)

ρ	k	Budget (\$ $\times 10^6$)							
		30	50	100	150	200	250	300	350
-0.9	10^{-5}	34.02	40.93	52.52	60.72	67.30	72.88	77.78	82.17
	10^{-6}	31.04	38.06	49.83	58.16	64.82	70.46	75.42	79.85
	10^{-7}	25.14	31.59	43.02	51.32	58.03	63.74	68.75	73.25
-0.5	10^{-5}	33.99	40.10	50.17	57.19	62.76	67.45	71.54	75.19
	10^{-6}	31.40	37.66	47.94	55.08	60.74	65.49	69.64	73.33
	10^{-7}	26.22	32.09	42.22	49.43	55.18	60.02	64.25	68.03
0	10^{-5}	33.88	38.93	47.06	52.61	56.95	60.58	63.72	66.50
	10^{-6}	31.84	37.05	45.39	51.06	55.49	59.18	62.36	65.19
	10^{-7}	27.75	32.75	41.11	46.90	51.45	55.24	58.52	61.43
0.5	10^{-5}	33.62	37.49	43.58	47.66	50.81	53.41	55.65	57.62
	10^{-6}	32.24	36.25	42.52	46.69	49.90	52.55	54.82	56.83
	10−7	29.58	33.48	39.82	44.11	47.42	50.16	52.50	54.57
0.9	10^{-5}	33.00	35.79	40.10	42.93	45.10	46.88	48.40	49.73
	10^{-6}	32.39	35.24	39.63	42.52	44.71	46.51	48.05	49.39
	10^{-7}	31.53	34.24	38.59	41.50	43.73	45.56	47.12	48.49