Optimal sourcing for controlling carbon emission - A case for sustainable supply chain

Abstract

Reducing the carbon footprint of global supply chains is a challenging attempt for many companies due to increasing government scrutiny and rising consumer awareness. Companies are therefore exploring ways to integrate carbon emissions into their operations, including the supply chain. This paper analyzes the company that sells multiple items, each source via different transportation modes, namely regular (slow) and expedited (fast). These modes differ in cost, transit time, and carbon footprint. The company needs to arrive at an optimal ordering quantity from each mode such that holding, backlog, and sourcing costs are minimal while the total transport carbon emission is below a particular target level. We take advantage of the dual index policy (DIP) and introduce the problem as a mixed integer linear problem, solving it through Dantzig-Wolfe decomposition. We compare our decision model against state-of-art approaches – Single mode selection and Dynamic mode blanket approach. We show that our approach exceeds benchmarks when products are sourced from different modes have low price differences, require low service levels, and exhibit high demand fluctuations. Our real-world data computational experiment shows that we outperform competing benchmarks by 15% and 40%, respectively.

Keywords: Dynamic Transport Modes, Sustainability, Multi-item assortment, Carbon emissions reduction

1. Introduction

Greenhouse gas emissions (GHGs) and its effect on climate change have been a major concern among various government institutions, policymakers, and environmentalists for decades. This problem was ratified globally in 1997 through the Kyoto Protocol was signed by industrialized countries to reduce GHGs emissions in the commitment period of 2008-2012 by at least 5% compared to 1990 levels. Several agencies found that Energy supply, Industry (manufacturing and industrial process) and Transportation sectors are among the top three most polluting sectors across Europe (European Environment Agency 2020). Of these, the Transportation sector has the dubious honor to uphold an upward trajectory (more than 19%) from the 1990 level in the EU (European Environment Agency 2020).

A similar trend is also observed in the US (US Environmental Protection Agency 2020). Recent analysis indicates that the G20 countries will experience a 60% jump in their transportation sector emissions by 2050 (Vieweg et al. 2018). Considering the above, The European Union (EU) has set an aggressive target to achieve 40% emission reduction by 2030 and achieve carbon neutrality by 2050 (European Environment Agency 2020). This resulted in an EU-wide Emission Trading Scheme (EU Emissions Trading System 2005) which enforces a cap on the total amount of GHGs emissions per sector per company (European Commission 2020). Companies exceeding these limits face a double risk of emission-related tax by the government as well as losing business from environmentally conscious customers (Dong et al. 2019). Therefore, companies are adopting different transportation policies to curb emissions in the transportation sector.

The transportation policies adopted by firms that sell a wide assortment of products (e.g., apparel, footwear, toys) sources from external suppliers predominantly follow two approaches namely Transport Mode Selection (TMS) (Hoen et al (2014a); ;Bouchery et al. (2016)) and Delivery Speed (DS) (Berling and Martínez-de Albéniz 2016) to curb emissions. The former combines transport modality decision and inventory policy simultaneously while the latter investigates optimal control policies for replenishment from two types of delivery speed (Slow and Fast). For example, Hewlett Packard (Beyer and Ward 2002) and Caterpillar (Rao et al. 2000) apply this strategy for replenishing supplies for server and work tools business respectively. In another case, Threatte and Graves (2002) studied the sourcing model of Polaroid Corporation which relies on ocean shipping for regular replenishments but uses air freight for expedited orders in the case risk of low inventory arises.

In the TMS, a vast literature is available that investigates the right transport mode based on several attributes such as cost, lead-time, accuracy etc, see Tyworth (1991), Engebrethsen and Dauzère-Pérès (2019) for a literature review of this field. Most recently, few authors (e.g., Palak et al. (2014); Hoen et al (2014a) ; Konur et al. (2017)) have included carbon emission as a third component in the cost vs lead-time trade-off. Palak et al. (2014) investigated the impact of carbon regulation on the replenishment decision of a firm using multi-mode transportation. Bauer et al (2013) and Winebrake et al. (2008) studies transport network design problems to minimize total emission due to freights. Blauwens et al. (2006) and Kiesmüller et al. (2005) investigated the effect of model shift and favor using a slow mode in addition to a fast one. Konur et al. (2017) explore order splitting among different transport modes to reduce GHG emissions. Hoen et al (2014a) propose a methodology to measure transport emissions and compare emission levels of different transport modes before deciding on a specific mode a priori (static mode) over a time horizon. In this direction, Hoen et al (2014b) extend the work of Hoen et al (2014a) by including a multi-item albeit in a single mode and deterministic setting. They show that carbon emissions can be reduced without a significant cost increase due to the portfolio effect of the entire assortment. Further, Lemmens et al. (2019) investigated dynamic switching between transport modes and observed reduced environmental impact without compromising on cost or service level.

Subsequently, DS refers to the adoption of two different transportation modes to replenish inventories. One is fast, costly, and more polluting than the supposedly regular and slow mode. Fukuda (1964) and Whittemore and Saunders (1977) were the first to investigate the dual-mode problem. They show that it is possible to arrive at the optimal policy when the lead-time difference between slow and fast mode is a one-time unit. However, for general lead-time cases, the optimal policy is complex and depends in general on the entire vector of outstanding orders. Sheopuri et al. (2010) consider DS as a special case of the classical lost sales inventory problem (KJ. Arrow and Scarf 1958) and show that simple order-up to policies are not optimal for dual-sourcing systems with a lead-time difference greater than one. To solve general lead-time cases two policies - Tailor Base-Surge (TBS) and Dual Index Policy (DIP) - have been extensively studied. The TBS orders a fixed amount per period from regular mode (ex-road or sea) to meet expected demand and relies on expedited mode (ex-air) following an order-up-to rule to manage the demand peaks (Allon and Van Mieghem 2010). The TBS policy draws similarities to the "constant order policy" introduced by Rosenshine and Obee (1976). Due to this similarity, the TBS policy monitors only one index. Janakiraman et al. (2015) provides numerical evidence that the optimality gap of the TBS policy shrinks as the lead time difference grows large. Therefore, we can infer that the TBS policy provides an asymptotic performance guarantee. However, TBS policy performs sub-optimal outside the asymptotic regime, particularly when the back-order cost increases or per unit cost of expedited order is large (Klosterhalfen et al. 2011). On the other hand, the DIP (Veeraraghavan and Scheller-Wolf 2008) is associated with two order-upto-levels and tracks both regular and expedited inventory positions. Veeraraghavan and Scheller-Wolf (2008) show numerically that DIP is optimal for a lead-time difference of one period and when the lead-time difference is large it performs close to optimality. The DIP offers higher flexibility compared to the TBS as it allows the order size of both modes to vary. Due to this property, DIP has received considerable attention from other researchers over the past decade (e.g., Arts et al. (2011); Sun and Van Mieghem (2019)).

The associated issues with TMS and DS are as follows. TMS-related studies investigate transport decisions using a single product and deterministic demand settings which is a major drawback considering how firms operate in practice. Existing literature on TMS combining dynamic mode selection, multi-product, and stochastic demand is rare. Whereas, in DS as the lead-time difference increases the state space of the problem grows exponentially. Finding a solution through dynamic programming for such complex problems is resource-intensive and computationally heavy. Therefore, researchers (e.g., Sheopuri et al. (2010) ; Klosterhalfen et al. (2011)) now rely on sub-optimal but well-performing heuristics such as the DIP to obtain optimal policy parameters tractably. Moreover, these optimal policy parameters are highly relevant to a firm that wants to meet carbon restrictions imposed by policymakers without compromising on cost and responsiveness. However, the DIP so far has been investigated in a single product setting without any emission constraints. Thus, this paper aims to study the effectiveness of a dynamic mode multi-item system under carbon constraints by answering the following key questions:

RQ1: How does one model and analyze the optimal decision-making for a single-echelon dynamic mode sourcing system considering multi-product assortment and combined emission constraints in a computationally efficient manner?

RQ2: How does the Dynamic mode multi-item approach perform compared to the alternative state-of-the-art approaches in terms of cost and emissions reduction?

RQ3: How do system parameters influence the relative performance of the dynamic mode multi-item sourcing approach?

To answer the first question, we find the base stock level of the entire assortment by formulating the decision problem as a non-linear non-convex problem. We rely on column generation to solve the decision problem, allowing us to decompose the multi-product problem into simpler single-product sub-problems. We can show that sub-problems constitute a newsvendor setting which we are able to solve efficiently through simulation procedures. For the second question, we compare the cost-emission trade-off of the dynamic mode selection approach with other leading approaches such as single-mode selection and blanket mode selection. To quantify the benefit of the portfolio effect, we use Blanket mode selection as an additional benchmark that enforces the emission constrain at the per-unit level. Blanket mode selection is a naïve approach in which the emission target is allocated per unit by dividing the total emission target by the total shipped products. We seek to estimate the incremental benefit the portfolio effect delivers over and above the naïve approach. Finally, we use real-world shipment data during numerical simulation to understand which model parameter dominates the efficient frontier of the dynamic mode multi-item approach.

To the best of our knowledge we are the first to explore and solve the multi-item sourcing problem under carbon emission regulation using a dynamic selection approach. We are different from other studies by incorporating a multi-product assortment under a stochastic setting. We use real-world shipment data from the apparel, footwear, and soft goods industries during numerical simulation to establish incremental benefits of the dynamic mode selection approach over single mode approaches. We show numerically that decomposing an aggregate carbon target into the individual target at the product level is financially less lucrative. Our holistic approach can lead to savings as high as 40% compared to benchmark approaches.

The remainder of the paper is as follows. First, the existing literature and the position of our work are described in section 2. Our model formation of the decision problem is described in section 3. The decomposition approach using column generation is described in section 4. We provide an account of the numerical simulation using real-world shipping data and compare the performance against the benchmark approaches in section 5. Finally, we conclude and highlight managerial insights in section 6.

2. Literature review

The two main research streams related to our work are Transport Mode selection (TMS) and Delivery Speed (DS) based classification . In the TMS stream, two distinct categories of literature emerge based on the modeling assumptions regarding the use of transport mode (Engebrethsen and Dauzère-Pérès 2019).The first category encapsulates a distribution system in which a single transportation mode is apriori selected before the start of a planning horizon. We identify this category as static mode selection. The majority of existing studies on inventory planning/distribution systems consider static mode transportation while modeling logistics costs (Engebrethsen and Dauzère-Pérès 2019). This topic was first explored by Baumol and Vinod (1970) who evaluated different transportation modes based on cost and lead time. Recently, carbon emission is gaining prominence as the third component in selecting the mode (Chen and Wang 2016). One of the pioneer researchers in this area, Hoen et al (2014a) study the inventory control policies of a firm where inbound logistics is managed by a 3PL with multiple transport modes at its disposal. They model the static mode selection problem such that it leads to the lowest long-term average cost consisting of ordering, holding, backlogging, and emission costs. Here, they consider stochastic demand albeit in a single product setting. They show numerically that for large distances rail and water transport are preferred mode and road transport is preferred in case of high density ($>$ 600 kg/m3) products. Hoen et al (2014b) extend the above study by considering a multi-item setting assuming average demand is known and inversely proportional to the sale price. They show numerically that substantial emission reduction (-10%) can be achieved with a slight increase (+0.7%) in logistics cost due to the portfolio effect of assortment-wide constraints. In both the above studies, a well-known carbon emission measurement methodology 'Network for Transport and Environment' (NTM) is used in modeling as it is based on real-world data mostly sourced from EU logistics service providers. In our study, we consider static mode selection as a competing state-of-the-art method to benchmark our proposed solution which is later discussed in detail.

The second category, dynamic mode selection concerns using multiple transportation modes simultaneously within a planning horizon. Thomas and Tyworth (2006) highlighted the benefits of combining multi-mode transportation both in terms of cost and emission savings and risk management during supply chain disruption. Aissaoui et al. (2007) studied closely related topics known as order splitting across multiple suppliers/transportation modes to meet total demand. They found that reduction of inventory holding cost and reduced stock out risk far exceeds the increase in transportation cost due to diseconomies of scale. Jain et al. (2011) found that combining two freight modes leads to significant cost savings over the best of two single freight models when the cost difference between two modes is minimal. Fan et al. (2017) highlighted that multi-mode transportation is beneficial for risk mitigation during periods of disruption. Hwang and Jaruphongsa (2006) studied a dynamic lot-sizing problem with two replenishment modes each having a distinct cost function and lead time under capacity considerations. They proposed a tractable algorithm to obtain the solution in polynomial time. Few researchers have extended this category by explicitly accounting for environmental impact. In this direction, Absi et al. (2013) extended the multi-mode lot-sizing problem by adding carbon emission constraints. They consider deterministic demand and a single item to model the problem. Later, Absi et al. (2016) extended the work of Absi et al. (2013) by considering dynamic demand and introducing fixed carbon emissions for each mode over and above unit emission. According to Palak et al. (2014), transport mode selection is impacted by the trade-off between cost and carbon emission. They evaluate models that capture the impact of carbon regulatory mechanisms – carbon cap, carbon tax, cap-and-trade, and carbon offset on transport mode selection. They show that in the event the carbon cap decreases and carbon tax increases, firms prefer to source from local suppliers who rely on truck transportation. Similarly, Konur and Schaefer (2014) investigated the impact of transportation mode choices on inventory control policies under different carbon regulations. They show numerically that for small value carbon trading price , retailers prefer high volume carriers (train, full truck freight) over Less-than-truckload (LTL) carriers to lower costs per unit time. However, for large α, LTL reduces both cost and emission. Further, under carbon offset and carbon emission tax regulation, a retailer would prefer a high-volume carrier over LTL as it reduces unit cost as well as emission. Konur and Schaefer (2014) adds a carbon cap to the classical EOQ policy by considering different inbound transportation modes. They observe that under stringent carbon cap constraints, retailers prefer to use heterogenous trucks to reduce carbon emissions while avoiding cost escalation. Pan et al. (2013) explored pooling supply chain networks using two modes i.e. trucks and rail to reduce carbon emissions. They observed that joint road and rail transport yields a relative reduction of 52% carbon emission. In DS a company primarily replenishes its stock from two transportation modes commonly referred to as regular (Slow) and expedited (fast). The assumption here is that an expedited mode has a shorter lead-time, but costs more compared to that of a regular one. Studies pertaining to companies adopting dual-mode sourcing are widely available. Allon and Van Mieghem (2010) studied a $10 billion high-tech U.S. company that sources inventory from suppliers in China and Mexico. The Chinese supplier (regular) has a longer lead time and lower replenishment costs than the Mexican (expedited) supplier. Similarly, Caterpillar Inc. orders the bulk of its materials from a regular supplier and places expedited orders from a local supplier when needed, but with a price premium (Rao et al. 2000). Beyer and Ward (2002) highlighted how HP benefited from implementing a dual-sourcing order policy and enjoyed low ordering costs without loss of flexibility. Fukuda (1964) and Whittemore and Saunders (1977) were the first to investigate this replenishment system. They show that the optimal policy of this system is complex even in the case of a single item. Although, dynamic programming can lead to optimal policy parameters however as the lead-time difference grows large the state space of the problem grows exponentially. Here, the ordering decision not only depends on the inventory position but also on all outstanding orders in the lead-time difference horizon. Thus, increasing computational power and processing time. To circumvent this issue, researchers have adopted sub-optimal but straightforward heuristic policies which are discussed below. The first set of policies to investigate are the Single-Index (SI) and Dual Index Policy (DIP). SI policies make regular and expedited order decisions based on one index or single state variable which is the inventory position (IP) over the entire lead-time horizon. SI first brings IP up to the expedited target level by placing an order via an expedited supplier and then brings the final inventory position (including the recent expedited order) up to the regular target level by ordering from a regular supplier. For general lead-time cases, Scheller-Wolf et al. (2007) analyzed the performance of SI policies via numerical experiments. They conclude that SI policies are easy to implement but usually underperform the DIP. However, in the case of large lead-time difference, SI is comparable to the DIP. Veeraraghavan and Scheller-Wolf (2008) proposed the DIP, which is more complex and tracks two inventory positions, one pertaining to regular and one for the expedited supplier. Like SI, DIP is associated with two order-up-to levels each for one supplier. In each period, the DIP first brings the expedited inventory position to its respective order-up-to level (S^e) by ordering from the expedited supplier. While keeping account of the recent expedited order, it then brings the regular inventory position to the regular order-up-to level (S^r) by ordering from a regular supplier. In the DIP, overshoot may occur when regular orders may push expedited inventory position above the expedited order-up-to level. Veeraraghavan and Scheller-Wolf (2008) verified that the overshoot relies only on the difference of order-up-to level (Δ=S^r-S^e) and is independent of expedited order-up-to level (S^e). This property allows us to obtain optimal policy parameters by one-dimensional search (e.g golden search) over Δ thereby identifying the optimal pair (Δ,S^e) in a computationally efficient manner. Another policy, Tailor Base Surge (TBS), originally due to Allon and Van Mieghem (2010), is a single index and single base stock policy. This makes TBS policy simple and highly tractable. Under TBS a fixed amount per period is ordered from the regular supplier to meet base demand and expedited order is placed using an expedited supplier following an order-up-to rule to address demand surges. Klosterhalfen et al. (2011) and Janakiraman et al. (2015) show numerically that the optimality gap of the TBS policy shrinks as the lead-time difference grows large. The intuition behind this result was put forward by Xin and Goldberg (2018) who show that as the lead-time difference grows large, a constant order which ignores the entire vector of outstanding orders performs close to optimality. Unfortunately, the TBS policy performs poorly, especially when the back-order cost is large, or the per-unit cost of the expedited supplier exponentially increases. These settings very much prevail in real business and therefore the effectiveness of the TBS policy in practice needs further investigation. The SI and TBS policies constrain companies to vary order across both channels to respond to changes in demand, cost, and service levels. The absence of such constraints makes the DIP favorable compared to other policies. Finally, we consider the DIP in our study because it is practical, intuitive, and can be optimized efficiently. Unlike our study, the DIP so far has been investigated in a single item setting and in absence of any carbon emission criteria.

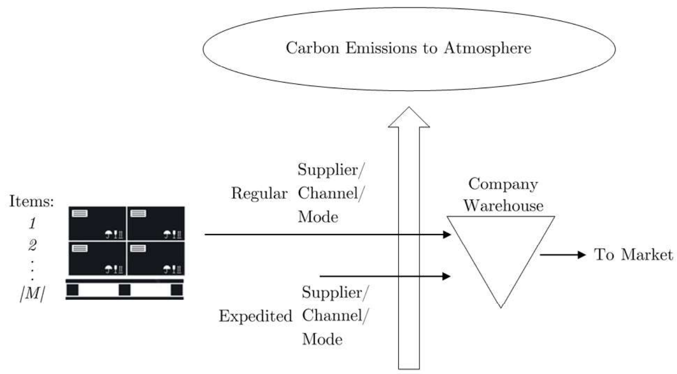
We focus on two papers that are closest to our study – Static mode selection Hoen et al (2014a) and the DIP (Veeraraghavan and Scheller-Wolf 2008). We extend the work of Hoen et al (2014a) in two ways. First, we consider dynamic mode selection (DMS) instead of single-mode selection (SMS), and second, we introduce a multi-product scenario to reflect how firms' source in practice. Further, we introduce a single constraint on the total average transportation emission from those assortments of products. Under special situations, the DIP can mimic static mode selection thus allowing us to establish the value addition of dynamic mode selection over static model selection. The benefit of the portfolio effect of multi-item emission constraint has already been established earlier albeit in a deterministic setting (see Hoen et al (2014b)).

3. Model

3.1. Inventory System

We consider a company that sells an assortment of products, each of which can be sourced either from a regular supplier or an expedited one. On one hand, the regular supplier is slower and cheaper than the expedited one. The problem at hand is to satisfy the demand which is stationary, yet stochastic such that total holding, backlog, and acquisition costs are minimized under a predetermined carbon emission cap. Each supplier is in charge of the transportation of the products to the company's warehouse, too, and does that through a distinct third-party logistic provider (3PL). Figure 1 is a schematic representation of the system under consideration.

Figure 1: A Single-Echelon Multi-Item Inventory System with Two Suppliers and Considering Carbon Emissions



Throughout the paper, we use three words 'supplier', 'channel', and 'mode' interchangeably and similarly words such as 'item', 'product', and 'SKU'.

We consider that demand for each item a non-negative random variable that is independently and identically distributed (i.i.d) and excess demand is backlogged. Let us denote the demand for item $m \in M$ in any time period t as $D_m(t)$. However, for practical purposes, we use the D_m random variable instead. Furthermore, we introduce $J = \{r, e\}$ the set of our regular and expedited suppliers. Hence, each supplier $j \in J$ has a deterministic lead time l_m^j and an acquisition cost c_m^j for item $m \in M$.The holding cost rate for any item $m \in M$ at the end of the period t is h_m and the company faces penalty cost p_m for each item back-ordered after demand fulfillment.

To replenish the products, the company takes advantage of a periodic review system over an infinite horizon, with the review period equals one time period and both lead times (regular and expedited ones) are integer multiples of the review period. The sequence of activities at each review takes place in this order: the arrival of orders, fulfillment of the backorders, ordering of inventory, placement, and satisfaction of demand, and finally cost assessment. During each period t the company orders from both modes. The alternative replenishment strategy is single-sourcing in which the company replenishes inventory from one of the two suppliers exclusively. In our analysis, we use single-sourcing to benchmark the performance of the dual-mode strategy.

For ease of reference, Table 1 provides all sets, parameters, and variables that are used in our analysis.

Table 1: List of Notations

	Sets:
M:	Set of items to be sourced or delivered
J:	Set of available sourcing channels/transportation modes/suppliers ($J = \{e, r\}$)
Π_m:	Set of available dual-index decision parameters π_m as $\Pi_m = \{\pi_m = (\Delta, S_m^{e^*}) : \pi_m \in (\mathbb{N}_0 \times \mathbb{Z}) \ \ \forall m \in M\}$
	Parameters:
h_m:	Holding cost rate for item $m \in M$, ($h_m \in \mathbb{R}^+$)
p_m:	Backorder penalty cost for item $m \in M$, ($p_m \in \mathbb{R}^+$)
c_m^j:	Acquisition cost of supply from channel $j \in J$ for item $m \in M$, ($c_m^j \in \mathbb{R}^+$)
c_m:	Difference between expedited and regular acquisition costs for item $m \in M$, ($c_m \in \mathbb{R}^+$)
l_m^j:	Lead time for supplying from channel $j \in J$ for item $m \in M$, ($l_m^j \in \mathbb{N}_0$)
l_m:	Difference of lead times for item $m \in M$, ($l_m = l_m^r - l_m^e$)
e_m^j:	Unit emissions for supply from channel $j \in J$ for item $m \in M$, ($e_m^j \in \mathbb{R}_{\geq 0}$)
β:	Maximum allowed total carbon emissions, ($\beta \in \mathbb{R}_{\geq 0}$)
β_m:	Maximum allowed carbon emissions for item $m \in M$, ($\beta_m \in \mathbb{R}_{\geq 0}$)
	General Variables:
D_m:	Random demand for item $m \in M$, ($D_m \in \mathbb{N}_0$)
$D_m(t_1, t_2)$:	Demand during the $[t_1, t_2]$ interval for item $m \in M$, ($D_m(t_1, t_2) \in \mathbb{N}_0$)
I_m:	Inventory level, ($I_m \in \mathbb{Z}$)
IP_m^j:	Inventory position for channel $j \in J$ and item $m \in M$, ($IP_m^j \in \mathbb{Z}$)
C_m:	Long run average cost per period for item $m \in M$, ($C_m \in \mathbb{R}^+$)
S_m^j:	Base-stock level for supplying from the channel $j \in J$ for item $m \in M$, ($S_m^j \in \mathbb{Z}$)
$S_m^{j^*}$:	Optimal base-stock level for supplying from the channel $j \in J$ for item $m \in M$, ($S_m^{j^*} \in \mathbb{Z}$)
ϵ:	Average long run total emissions per period, ($\epsilon \in \mathbb{R}_{\geq 0}$)
ϵ_m:	Average long run emissions per period for item $m \in M$, ($\epsilon_m \in \mathbb{R}_{\geq 0}$)
	Dual-Sourcing Variables:
q_m^j:	Order quantity from the channel $j \in J$ for item $m \in M$, ($q_m^j \in \mathbb{N}_0$)
O_m:	Inventory position overshoot of item $m \in M$, ($O_m \in \mathbb{N}_0$)
Δ_m:	Dual-index parameter for item $m \in M$, ($\Delta_m \in \mathbb{N}_0$)
$\tilde{D}_m(t_1, t_2)$:	Net demand during the $[t_1, t_2]$ interval, ($\tilde{D}_m(t_1, t_2) \in \mathbb{N}_0$)
π_m:	Member of Π_m
π_m^k:	$\mathrm{k^{th}}$ member of Pi_m
x_m^k:	Binary decision variable for dual-sourcing with policy $\pi_m^k \in \Pi_m$, ($x_m^k \in \{0, 1\}$)
	Single-Sourcing Variables:
C_m^j:	Long run average cost per period for single-sourcing from channel $j \in J$ for item $m \in M$, ($C_m^j \in \mathbb{R}^+$)
y_m^j:	Binary decision variable for single-sourcing from channel $j \in J$ for item $m \in M$, ($y_m^j \in \{0, 1\}$)

3.2. Carbon Emission Modeling

Before continuing with our model, in this part, we introduce how we model carbon emission for our further analysis. We assume that the sole source of emissions is transportation.

We use The GLEC framework Greene and Lewis (2019) to calculate the carbon emission. We use a standard unit CO_2-Equivalent (CO_2e) to account for different greenhouse gases effect. Greene and Lewis (2019) recommends three potential scopes for carbon emission estimation: Scope 1 includes all direct CO_2 emissions of a company. Scope 2 contains indirect CO_2 emission caused by energy sourced externally, e.g., electricity, heating. Finally, Scope 3 include all indirect CO_2 emission especially that of freight transportation. Greene and Lewis (2019) adopts an entire fuel life cycle for carbon accounting from the source of energy (the well) through the energy extraction until the point of use (the tank), also known as the Well-to-Tank (WTW) accounting method. Since our focus is transportation-related emissions, we will delve deeper into Scope 3 calculations. Scope 3 calculations require a specific metric - 'tonne-kilometer that considers both weight (actual mass in tonne) and the distance. GLEC provides a detailed guideline to capture distance accurately and consistently, considering real operating conditions.

To calculate Scope3 CO_2 emission, we multiply tonne-kilometer (tkm) and the average CO_2 emitted per tonne-kilometer (tkm) also known as the CO_2e intensity factor. GLEC (Greene and Lewis 2019) module2 lists CO_2e intensity factor of all transport modes (sea, air, and road) along with different combination of vessel (Container vessel, Long haul flight) and fuel type (Diesel, CNG, LPG).

Thus, carbon emission estimation is given by:

kgCO_2 emission $= \sum_1^n$(total tkm $\times$ CO_2e intensity factor)

Let us explore a simple case study to understand the above formulae. We consider an apparel order that is shipped from Vietnam to the US. The details of the shipment is as following

1. Quantity = 5000 pieces
2. Weight per piece = 750 gms (0.00075 tonne)
3. Planned (Nautical) distance between Vietnam and US = 24,000 km

4. CO_2e intensity factor = 20 gm/tonne-km (Assuming a Cargo < 10dwkt ship)

Step wise CO_2e calculation of the shipment is as below :

Total $tonne - km$ = 5,000 $\times$ 0.00075 tonne $\times$ 24,000 km = 90,000 tkm

Total CO_2e = Total $tonne - km$ $\times$ CO_2e intensity factor

= 90,000 tkm $\times$ 0.02 kg/tkm = 1,800 kg

3.3. Decision Making Problem

Let us come back to our model. As we mentioned our model is a single-echelon periodic review inventory system with two suppliers and stochastic demand. For an item $m \in M$, let the on-hand inventory and the back-order at the end of time period t be I^+ and I^-, respectively. Accordingly, we can calculate the long run average total cost per period C_m for the item m as follows:

$$C_m = \sum_{j \in J} c_m^j E[q_m^j] + h_m E[I_m^+] + p_m E[I_m^-] \tag{1}$$

where q_m^j is the order quantity for item m from a channel $j \in J$. The company's main decision-making problem is to minimize the long-run average total cost for all items by wisely selecting the order quantities provided that the system's average carbon emission per period does not surpass a certain target. Mathematically, We formulate this problem as:

$$\begin{aligned} &\min_{q_m^j(t):m \in M, j \in J} \quad \sum_{m \in M} C_m \\ &\text{Subject to} \quad \epsilon \leq \beta \end{aligned} \tag{2}$$

where β is the target average CO_2e per period and ϵ is the expected total emissions per period from the system. ϵ is the sum of the expected emissions per period for all items from both channels. In this sense let ϵ_m be the expected total emissions per period for procuring an item $m \in M$ and e_m^j denote the amount of emissions produced by supplying one unit of the m from a channel $j \in J$. We assume that e_m^j is constant. Therefore,

$$\epsilon_m = \sum_{j \in J} E[q_m^j] e_m^j \tag{3}$$

and

$$\epsilon = \sum_{m \in M} \epsilon_m = \sum_{m \in M} \sum_{j \in J} E[q_m^j] e_m^j \tag{4}$$

Among the possible alternative approaches to address our problem there are three from the literature with better performance. These are single-sourcing item-wise, single-sourcing multi-item (mode-selection) and Dual mode item-wise (blanket) methods. By item-wise approaches we make a decision for each item, independently, without considering other items. Hoen et al (2014a) established that the single-sourcing mode-selection outperforms the single-sourcing item-wised approach, and therefore is out of our consideration. We benchmark the dual-mode multi-item approach against the remaining two approaches to evaluate their relative performance. In terms of the mathematical formulation, the single-sourcing mode-selection is a special case of the problem 2 with the exception that in the single-sourcing strategy the expected order quantity $E[q_m^j]$ for item $m \in M$ from the supplier $j \in J$ is either $E[D_m]$ or zero. For the dual mode item-wise (blanket) approach, we define the cost minimization problem for items $m \in M$ as

$$\begin{aligned} &\min_{q_m^j(t): j \in J} \quad C_m \\ &\text{Subject to} \quad \epsilon_m \leq \beta_m \end{aligned} \tag{5}$$

Here, each β_m is a fraction of β which is calculated by applying the overall carbon reduction target to to per item m level.

In the next section we explain how we calculate the long run average cost under certain policies and solve the general optimization problems 2 and 5.

4. Analysis

In this section we first introduce our approaches to calculate inventory policies related to the dual-sourcing and single-sourcing. Then, we utilize these approaches the solve the optimization problems that as discussed in sub-section 3.3. We also introduce our techniques to solve the optimization problems.

4.1. Dual mode selection Heuristic

In the DIP, inventory is replenished from a regular supplier at cost c_m^r per unit and/or from an expedited supplier at a higher cost c_m^e (i.e $c_m^e > c_m^r$). We consider that lead time (l_m^r) of regular source is longer than that of expedited one (l_m^e). For notational convenience, difference of supplier lead time l_m is defined as l_m^r - $l_m^e \geq 1$.

Let $I_m(t)$ be the remaining on-hand inventory at the beginning of period t post-arrival of orders, but before demand $D_m(t)$ has occurred. Let q_m^r, q_m^e be the order size placed with the regular and expedited supplier at period t respectively. A holding cost h_m per unit is levied on on-hand inventory $(I_m(t)$-$D_m(t))^+$ at the end of a period. Similarly, cost p_m per unit is associated with backlog $(D_m(t)$-$I_m(t))^+$. For simplicity, we initiate backlog and on-hand inventory at period t_0 at zero value.

Total demand is the sum total of order quantities from both channels.

$$E[D_m] = E[q_m^e] + E[q_m^r] \tag{6}$$

As $c_m^r E[D_m]$ is a constant that cannot be influenced by inventory order decisions, the equation 1 can be reduced to

$$C_m = c_m E[q_m^e] + h_m E[I_m^+] + p_m E[I_m^-] \tag{7}$$

where $c_m = c^e_m - c^r_m$.

In this policy, two order-up-to levels are used one for the regular (S^r_m) supplier and one for the expedited (S^e_m) one. We carry two inventory positions IP^e_m (for expedited) and IP^r_m (for regular). The inventory position at a given period t is defined as the net inventory level at the end of period $t-1$ plus outstanding orders arriving within the respective lead time. To determine inventory replenishment policies for the expedited mode we first check IP^e_m and order from the expedited channel so that the expedited inventory position does not go below the expedited order up to level S^e_m.

$$IP^e_m(t) = I_m(t-1) + \sum_{i=t-l^e_m}^{t-1} q^e_m(i) + \sum_{i=t-l^r_m}^{t-l_m} q^r_m(i) \tag{8}$$

where $l_m = l^r_m - l^e_m$. We set S^r_m so that the total inventory position at time period t after ordering $q^e_m(t)$ does not go below regular up-to level.

$$IP^r_m(t) = I_m(t-1) + \sum_{i=t-l^e_m}^{t} q^e_m(i) + \sum_{i=t-l^r_m}^{t-1} q^r_m(i) \tag{9}$$

The maximum value of $q^r_m(t)$ is given by $\Delta_m = S^r_m$-S^e_m and the order quantities are $q^e_t = (S^e_m$-$IP^e_m)^+$ and $q^r_m(t) = S^e_m$ - IP^r_m for expedited and regular channel respectively. It is to be noted that in the DIP the expedited inventory position in period t can exceed the order-up-to level S^e_m, representing an overshoot (O^t_m). This happens when regular order placed t=l^r_m-l^e_m periods ago enters the information horizon. Hence, $O_m(t)$ is defined as $IP^e_m(t)$ + $q^e_m(t)$ - S^e_m i.e (IP^e_m-$S^e_m)^+$. In the presences of an overshoot, no expedited ordering is made but in a deficit ($IP^e_m < S^e_m$) situation an order $q^e_m(t) = S^e_m$ - $IP^e_m(t)$ is made to restore the inventory position back to S^e_m. To understand the overshoot behaviour we further explore various system properties involving $O_m(t)$, IP^e_m, S^e_m, q^e_m and q^r_m. We can deduce the following:

$$IP^e_m(t+1) = IP^e_m(t) + q^e_m(t) + q^r_m(t-(l-1)) - D_m(t) \tag{10}$$

$$\Rightarrow IP^e_m(t+1) = O_m(t) + S^e_m + q^r_m(t-(l-1)) - D_m(t) \tag{11}$$

Using 11 in the expression $O_{t+1} = (IP^e_{t+1}\text{-}S_e)^+$ where the $+$ operator is defined as $x^+ = \max(x,0)$, we can deduce

$$O_m(t+1) = (O_m(t) + q^r_m(t-(l-1)) - D_m(t))^+ \tag{12}$$

Further, we can deduce the expression for $q^r_m(t+1)$ and $q^e_m(t+1)$ as :

$$q^e_m(t+1) = (D_m(t) + O_m(t) - q^r_m(t-(l-1)))^+ \tag{13}$$

$$q^r_m(t+1) = O_m(t+1) - \Delta_m + \sum_{i=t-l}^{t} q^r_m(i) \tag{14}$$

From 14 we can infer that the overshoot $O_m(t)$ is independent of S^e_m and a function of Δ_m.

Due to the possibility of an overshoot at each time period, we calculate the inventory level at time $t \in T$ as

$$I_m(t) = IP^e_m(t-l^e_m) - D_m(t-l^e_m,t) = S^e_m - (D_m(t-l^e_m,t) - O^{\Delta_m}_m(t-l^e_m)) \tag{15}$$

where $D_m(t_1,t_2)$ is demand over the time interval $[t_1,t_2]$ including t_2-t_1+1 time periods and $O^{\Delta_m}_m(t)$ is the overshoot at time t due to Δ_m. We call the random variable $D_m(t,t+l^e_m) - O^{\Delta_m}_m(t)$ net demand and represent it with $\tilde{D}_m(\Delta_m)$. According to Veeraraghavan and Scheller-Wolf (2008) expedited order-up-to decision in this setting represents a newsvendor problem. For each Δ_m, we calculate the optimal $S^{e^*}_m(\Delta_m)$ as the newsvendor fractile of the net demand D̃ as the convolution of the demand over l_e+1 period with stationary overshoot.

$$P\{\tilde{D}(\Delta_m) \leq S_m^{e^*}\} = \frac{p_m}{p_m + h_m} \tag{16}$$

Further, we calculate $S_m^{r^*} = S_m^{e^*}(\Delta_m) + \Delta_m$. We then find cost of each pair of $(\Delta_m, S_e^*(\Delta))$. The optimal parameters are obtained from the expression

$$(\Delta_m^*, S_m^{e^*}(\Delta_m^*)) = \arg\min_{\Delta_m} C_m(\Delta_m, S_e^*(\Delta_m)) \tag{17}$$

by performing a uni-dimensional search over Δ_m . For dual-index parameter Δ_m, the optimal average long run total cost and the associated average long run emissions is calculated by combining equations 7, 15, and 16, and 17.

$$C_m(\Delta_m) = c_m E[q_m^e(\Delta_m)] + h_m E[(S_m^{e*}(\Delta_m) - \tilde{D_m}(\Delta_m))^+] + p_m E[(\tilde{D_m}(\Delta_m) - S_m^{e*}(\Delta_m))^+] \tag{18}$$

and the emissions for this optimal policy is

$$\epsilon_m = \sum_{j \in J} E[q_m^j(\Delta_m)] e_m^j \tag{19}$$

4.2. Single-Sourcing Base-Stock Policies

For a single-sourcing single-echelon inventory system with periodic review and stochastic demand, we know that a base-stock policy from the solution of the related newsvendor problem is optimal (Axsäter 2006). In other words for single-sourcing an item $m \in M$ from the channel $j \in J$ the average long run total cost C_m^j is

$$C_m^j = c_m^j E[D_m] + h_m E[(S_m^{j^*} - D_m(t, t + l_m^j))^+] + p_m E[(D_m(t, t + l_m^j) - S_m^{j^*})^+] \tag{20}$$

where $S_m^{j^*}$ is the optimal base-stock level and $D_m(t, t+l_m^j)$ is demand over lead time including $l_m^j + 1$ time periods. According to the result of the newsvendor problem, we calculate the optimal base-stock level $S_m^{j^*}$ through the following relation

$$Pr(D_m(t, t + l_m^j) \leq S_m^{j^*}) = \frac{p_m}{p_m + h_m} \tag{21}$$

4.3. Optimization Methods

In this part we explore efficient ways to solve the non-linear optimization problems 5 and 2. We first explore approaches related to dual mode problem and then proceed with the single-sourcing mode-selection problem. We make use of equations 18 and 19 to offer the solution strategies for dual-souring multi-item and blanket approaches. But before that we introduce additional notations that is used frequently for analyzing the dual-sourcing optimization problems. For a dual-sourcing system with multiple items, $\Pi_m = \{\pi_m = (\Delta, S_m^{e^*}) : \pi_m \in (\mathbb{N}_0 \times \mathbb{Z}) \ \ \forall m \in M\}$ is the set of all available π_m which are the pairs of dual-sourcing decision parameters Δ_m and their associated optimal expedited base-stock level resulting from equation 16. In addition we consider π_m^k as the k$^{\text{th}}$ member of Π_m $(k \in \mathbb{N})$.

Now, we address the optimization problems with the dual-sourcing multi-item approach. The problem 2 is a special case of nonlinear knapsack problem which is NP-hard. One way of dealing with this kind of optimization problems is using Dantzig-Wolfe decomposition (column generation) technique (Dantzig and Wolfe 1960). In this method we first reshape the problem into an integer programming (IP) one wherein the cost function and left hand side of constraints act as the coefficients of binary decision variables. In our case for each $\pi_m^k \in \Pi_m$ we define a binary variable x_m^k that is one if the k$^{\text{th}}$ policy is selected and zero otherwise. Then the objective function is the sum of all those binary decision variables with $C_m(\pi_m^k)$ as the multiplier and the left handside of the emissions constraint is the sum of all binary decision variables with the coefficient of $\epsilon_m(\pi_m^k)$. For each item, we select one and only one policy. Since the computation of all those coefficients to input into the IP problem is inefficient, we first formulate a linear relaxation form of the IP problem called the master problem. Then, in a recursive manner, we form and solve another $|M|$ problems (sub-problems) which are decomposed in items and utilize their optimal policies as the new columns to the master problem. By increasing the number of columns, the optimal objective of the master problem converegs to the optimal objective of the problem 2. We continue these recursions until a stopping criteria occurs. For our case the master problem is

(MP - Equation 22)

$$\min_{x_m^k: m\in M, k\in\mathbb{N}} \sum_{m\in M}\sum_{k\in\mathbb{N}} C_m(\pi_m^k)x_m^k \tag{22a}$$

$$\text{Subject to} \quad \sum_{m\in M}\sum_{k\in\mathbb{N}} \epsilon_m(\pi_m^k)x_m^k \leq \beta \tag{22b}$$

$$\sum_{k\in\mathbb{N}} x_m^k = 1 \qquad \forall m\in M \tag{22c}$$

$$x_m^k \geq 0, \qquad \forall m \in M, \forall k\in\mathbb{N} \tag{22d}$$

where C_m and ϵ_m come from the equations 18 and 19. Let λ and ν_m denote dual variables for constraints 22b and 22c, respectively, then the sub-problem m is

(SUB(m))

$$\min_{\pi_m^k: m\in M, k\in\mathbb{N}} \quad C_m(\pi_m^k) - \lambda\epsilon_m(\pi_m^k) - \nu_m \tag{23}$$

The sub-problem 23 can be expanded based upon equations 18 and 19

$$\begin{aligned}\min_{(\Delta_m, S_m^{e*})\in\Pi_m} (c_m - \lambda e_m^e)E[q_m^e(\Delta_m)] - \lambda e_m^r E[q_m^r(\Delta_m)] + h_m E[(S_m^{e*}(\Delta_m) - \tilde{D}_m(\Delta_m))^+] \\ + p_m E[(\tilde{D}_m(\Delta_m) - S_m^{e*}(\Delta_m))^+] - \nu_m\end{aligned} \tag{24}$$

Evidently, equation 24 is a newsvendor problem itself for a given parameter Δ_m which can be solved by a search over the available parameters. The column generation recursive approach starts with an initial set of feasible solutions, for instance the set of least polluting single-sourcing policies. In each iteration we first solve the master problem 22 and find the dual variables λ and ν_m. Next, for each item m, using the λ and ν_m we setup the reduced cost sub-problem 24. Using the sub-problems we decompose the master problem (multi-item) into several single-item problems. Then we search over the dual-sourcing parameters to find the optimal policies of the sub-problems. In case of negative reduced cost, these optimal policies are added as new columns to the master problem in order to generate new dual variables (λ and ν_m). We continue these recursions until no optimal policy of sub-problems leads to a negative reduced cost. We note that the column generation method is also applicable to a dual-sourcing system where multiple heuristics are applied for each item. Unlike the dual-sourcing multi-item approach, the optimization model for the dual-sourcing blanket approach is basically decomposed for items as explained in section 3. So for each item $m \in M$ we formulate the optimization problem as:

$$\begin{aligned} &\min_{k \in \mathbb{N}} \quad C_m(\pi_m^k) \\ &\text{Subject to} \quad \epsilon_m(\pi_m^k) \leq \beta_m \quad m \in M, k \in \mathbb{N} \end{aligned} \tag{25}$$

where, C_m and ϵ_m come from the equations 18 and 19, respectively. Obtaining the optimal policies for the dual-sourcing blanket approach is not sophisticated in view of the fact that the optimization problem is already decomposed in items. Among different methods we make use of searching for the policies with the closest emissions to the target one.

We wrap up our discussion in this part with the single-sourcing mode-selection approach. Considering the fact that in single-sourcing mode-selection problem we have finite number of items in a problem and for each item we opt simply one mode among the available two, and taking advantage of the exact newsvendor optimal solution 20 and 21, we first calculate the cost and emissions of optimal policies for each mode of each item individually and then solve the problem 2 as an integer programming (IP) problem. In this case let y_m^j a binary variable associated to item $m \in M$ and mode $j \in J$ which is 1 if the mode j is selected for item m and zero otherwise. Then the problem 2 can be reformulated as

$$\begin{aligned}
&\min_{y_m^j: m \in M, j \in J} \sum_{m \in M} \sum_{j \in J} C_m^j y_m^j \\
&\text{Subject to} \sum_{m \in M} \sum_{j \in J} E[D_m] e_m^j y_m^j \leq \beta \\
&\qquad \sum_{j \in J} y_m^j = 1 \qquad\qquad \forall m \in M \\
&\qquad y_m^j \in \{0, 1\} \qquad\qquad \forall m \in M, \forall j \in J
\end{aligned} \tag{26}$$

for which C_m^j is calculated through equations 20 and 21. The outcome of this approach is exact, yet for very large number of items it would be inefficient. In that case other alternatives such as utilizing a greedy heuristic is handy.

5. Numerical study

In this section we conduct a numerical study to examine the relative performance of the three decision making approaches modeled in the section 3 and analyzed in the section 4 constrained by a set of emissions reduction targets over the same testbeds. Afterwards, we scrutinize how making alterations to parameters affect the total cost of each approach as well as the relative performance of them. We benchmark the dual-sourcing multi-item method and compare the single-sourcing mode-selection and the dual-sourcing blanket with that. Before these two steps we give an explanation for how we calculate the unit emissions.

5.1. Unit Emissions

Greene and Lewis (2019) shows that the transport carbon emission depends on both transport parameters such as mode, vehicle type, distance traveled, and load factor as well as product parameters volume and weight. For the latter, we choose two product categories

- Apparel and Auto-component to show heterogeneity in volume and weight. We retrieve shipment data of the above two categories from a public website (https://comtrade.un.org) using a unique combination of 100 HScodes. We consider two different dual-sourcing environments - Sea vs Air shipment (for Apparel) and Road vs Sea (for Auto-components). We take advantage of the CERDI database (www.ferdi.fr/en/indicators/the-cerdi-seadistance-database) and other public databases to estimate nautical, air, and road distance between two destinations. We assume vehicle type and fuel type for each mode for estimating carbon emission using the GLEC framework. We calculate per unit carbon emission for 100 items using the approach mentioned in section 3.2. Using the apparel shipment data set, we present a scenario wherein a US company sources products from Vietnam using a regular (sea) and an expedited (air) mode. Similar, using auto-component data, we present a dual-sourcing setting of a US company sourcing from Mexico and China representing expedited (road) and regular (sea) mode respectively.

After calculating per unit emission, we obtained three cases :

1. Apparel shipment using Sea and Air freight : $e_e > e_r$
2. Auto-component shipment using Road and Sea : $e_e < e_r$
3. Combined data (to represent heterogeneity) : Two of the above

We use Maximum Likelihood Estimate (MLE) technique to identify distribution of the real world unit emission data. Parameters of such distributions are provided in Table 2.

5.2. Computational Implementation

In this numerical study two approaches, namely, single-sourcing mode-selection and dual-sourcing blanket are considered against which the performance of dual-sourcing multi-item is compared. In this part, we first explain how dual-sourcing policies are calculated and then elaborate on the three optimization engines that are utilized for each of the three approaches. Dual-sourcing policies are calculated based on the dual index heuristic as explained in the section 4 and the simulation of demand arrays so that a 95% confidence interval for the cost

Table 2: Parameters for Base and Parametric Analysis Testbeds

	Distribution	Base Analysis Parameters	Parametric Analysis Changed Parameters	Parametric Analysis Instances
Demand(D) $\sim$ Negative Binomial(μ_D, CV_D)				
μ_D	Gamma	mean=100 CV_{μ_D}=50	$CV_{\mu_D} = CV_h$ $\in \{0.3, 0.4, 0.6, 0.7\}$	1 through 4
CV_D	Shifted Beta (+ $min\ \ CV_D$)	mean=0.9 std=0.25 $min\ \ CV_D$=0.3	$min\ \ CV_D$ $\in \{0.2, 0.25, 0.35, 0.45\}$	9 through 12
h	Gamma	mean=1 $CV_h = CV_{\mu_D}$ $\rho_{\mu_d,h} = -0.5$	$\rho_{\mu_d,h}$ $\in \{-0.3, -0.4, -0.6, -0.7\}$	5 through 8
l	Fixed	3	$l \in \{2, 4\}$	13 through 14
$p = c_p X h$				
X	Shifted Beta (+ 0.02)	mean=0.98 std=0.1	-	-
c_p	Fixed	20	$c_p \in \{3, 4, 5, 9, 19, 99\}$	15 through 20
$c_e = xpl$				
x	Beta	mean=0.25 std=0.1	mean $\in \{0.15, 0.2, 0.3, 0.35\}$	21 through 24
Case 1 ($e_e = e_r + diff, diff \geq 0$)				
e_r	Std. Gamma	α=7.88 β=0.05	-	-
$diff$	Log-Normal	μ=1.68 σ=0.36	scale factor on $diff$ $\in \{0.8, 0.9, 1.1, 1.2\}$	25 through 32
Case 2 ($e_r = e_e + diff, diff \geq 0$)				
e_e	Std. Weibull	k=0.59 λ=0.71	-	-
$diff$	Std. Gamma	α=0.46 β=2.39	scale factor on $diff$ $\in \{0.8, 0.9, 1.1, 1.2\}$	25 through 32
Case 3 (combined)				
e_r	Log-Normal	μ=0.05 σ=1.48	$min(e_r, e_e)$ fixed scale factor on $\lvert e_r - e_e \rvert$ $\in \{0.8, 0.9, 1.1, 1.2\}$	25 through 32
e_e	Std. Gamma	α=0.66 β=5.99		

of each policy is kept less than three percent of the average cost per period from the samples. In order to do that, for each item m, a demand array is generated by a common random number generator and then, for a certain DI parameter Δ_m, the order quantities from the regular and expedited suppliers along with the overshoot are simulated based on recursive equations 12 through 14. Having calculated the overshoot, we select the optimal expedited order-up-to level using the newsvendor problem 16. For each simulation, a confidence interval is computed across 10 samples of 9,500 time periods following a 5000 time window warm-up. The long run average cost is the average of the mean cost per period of the 10 samples.

We know that for each item a DI policy with $\Delta = 0$ is equivalent to single-sourcing from the expedited supplier and if $\Delta \to \infty$ and $S^e \to -\infty$ the single-sourcing from the regular supplier. However, we do not associate one of these two policies to the maximum dual-sourcing emissions. Indeed, that is produced by the global optimal policy as others with higher pollution cannot improve the cost. To find such an optimal policy for each item we use a uni-directional search over Δ, taking advantage of the golden-section algorithm. Additionally, for the matter of consistency, we generate the single-sourcing policies used in the mode-selection integer programming through dual-sourcing with appropriate parameters.

We take advantage of Gurobi solver to solve optimization problem related to dual-sourcing multi-item and single-sourcing mode-selection approach.

5.3. Results

5.3.1. Base cases

The numerical analysis starts with three base cases and continues with parametric analysis over each testbed. The rationale behind partitioning numerical experiments between three cases stems from the fact that different industries face circumstances where for an assortment of items the emissions from the regular modes with respect to the expedited ones would be lower (or equal), higher (or equal), or combined. Our cases, too, are formed in the same order. The real-world unit emission data is collected from apparel and auto-component sectors on which appropriate distribution functions are fitted as discussed in subsection 5.1.

Another real aspect that we considered in shaping our testbeds is the correlation between demand and holding cost where the higher the demand, the lower the holding cost. Consequently, we assume that mean demand μ_D and holding cost h are correlated with Pearson's correlation measure $\rho = -0.5$ have the same coefficients of variation $CV_{\mu_D} = CV_h$ of 0.5. All parameters for generating the base testbeds from common random number generators are introduced in Table 2. Seeing that in our analysis only the difference between the expedited and the regular lead times and acquisitions costs are relevant, for the rest of the numerical study we take $l_e = 0$ and $C_r = 0$ and use $l = l_r - l_e$ and c_e for computations. Moreover, the back-order penalty cost is a function of the holding cost $p = c_p h X$ and the expedited acquisition cost is a function of the back-order penalty cost $c_e = xpl$ where X and x are two independent random variables as provided in the Table 2. As a consequence the service level equals to $\frac{c_p X}{c_p X+1}$.

All testbeds including the base ones are composed of 100 items. To generate correlated random numbers such as mean demand and holding cost, we take advantage of a Gaussian copula with a fitting covariance matrix.

The base testbeds are input data for determining efficient frontiers of the three sourcing techniques for certain emissions reduction targets on reducible emissions. By reducible emissions we mean the difference between the total amount of emissions that the most cost-efficient inventory policies bring about without any emissions constraint, and that of the least polluting policies which are the selection of least polluting single-sourcing modes. It is evident that the most cost-efficient policies under no emissions constraint are offered by dual-sourcing approaches for the reason that the single-sourcing is a special case of dual-sourcing, being considered by dual-sourcing approaches as a feasible solution during optimization. We set 28 emissions reduction percentage targets including $\{0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 93, 95, 96, 97, 98, 99, 99.5, 99.8, 100\}$ to compute efficient frontiers for the three base testbeds. Upon solving these base cases for efficient frontiers we can observe that dual-sourcing multi-item outperforms the other approaches significantly (Figure 2). Figures 3 illustrate that in all cases mode-selection approach is more than 8% more expensive than the dual-sourcing ones with no emissions constraint and the slope of reducing this gap between the mode-selection and multi-item approaches remains low even up to 50% reduction target. In case 1 where the emissions from the expedited mode is more than the regular one, mode-selection method exhibits no flexibility by selecting only the least polluting modes (Figure 2a), whereas both dual-sourcing approaches can provide several considerably cheaper policies (Figure 3a). As case 1 is ubiquitous in supply chains, this result suggests that even without paying attention to the cumbersome emissions reduction optimization computations, common dual-sourcing heuristics outperform the single-sourcing optimal solutions from the economic and also environmental point of views, owing to the capacity of dual-sourcing heuristics to keep ordering from the regular supplier under uncertain demand.

However, Cases 2 and 3 (Figures 3b and 3c) make clear that the application of dual-sourcing naively, such as using the blanket approach, can even trigger a higher cost than single-sourcing. In other words, it is only the dual-sourcing multi-item approach that can in all cases outperform the single-sourcing mode-selection approach. Fortunately, this dominance remains until high emissions targets. For instance, mode-selection optimal solutions cost more than 5% than dual-sourcing multi-item ones until reduction targets around 75% in all cases which is significantly high. At 50% carbon reduction target the dual-sourcing multi-item has the advantage of 7.25% in case 1, 7.39% in case 2, and 7.81% in case 3 over single-sourcing mode-selection which are quite significant. Seemingly, other better performing dual-sourcing heuristics such as projected expedited inventory position heuristic (Drent and Arts 2022) can reach the same targets at even lower costs. The results of base case computations and provided in Appendix A.

5.3.2. Parametric analysis

In this section, we study the impact of changing parameters on the comparative performance of the dual-sourcing multi-item approach with respect to dual-sourcing blanket and single-sourcing mode-selection methods. The changed parameters are brought in Table 2. The first 28 instances are examined based on 50% reduction of the reducible emissions arising from that testbed. In addition, we analyze instances 25 through 28 to reach 50% of the reducible emissions of the associated base testbeds (instances 29 through 32). All these 32 instances are computed for three cases resulting in totally 96 parametric analysis instances. The results of this analysis are provided in Appendix B and represented in Figures 4 and 5.

The impact of increasing (or decreasing) the coefficient of variation of mean demand and the holding cost (instances 1 through 4) brings about an analogous pattern over the three

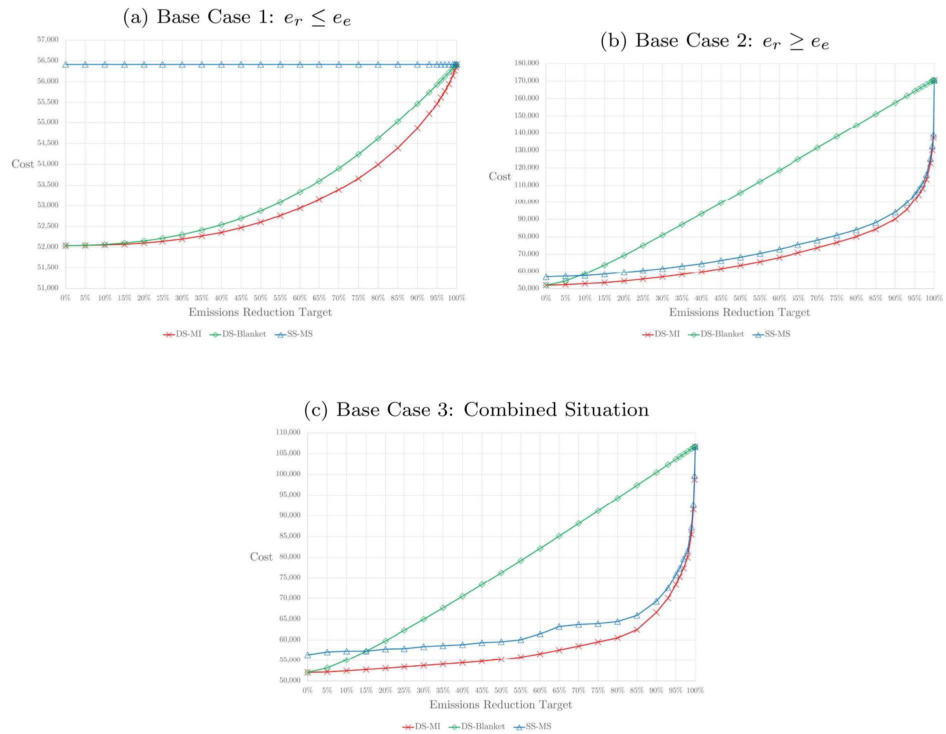


Figure 2: Efficient frontiers for the three base cases given the target on reducible emissions

approaches within all cases. As it is clear in Figure 4 the CV_{μ_D} change drives the cost in the opposite direction, in that on the one hand the μ_D and h are negatively correlated and on the other hand p and c_e are correlated to h positively. In case the CV_{μ_D} increases we have more items with higher μ_D and consequently lower h and more items with lower μ_D and higher h, while the mean of mean demand remains the same. That implies that the demand for cheaper items grows, while that of more expensive items declines. Because of the similar cost impact for the three approaches, their relative differences do not change significantly (Figure 5). Additionally, We can observe the same circumstances in instances 5 through 8 where the correlation decreases.

Instances 9 through 12 indicate the more demand variability the more the cost in all items as the expedited orders, backorders, and inventory on hand climb. However, this

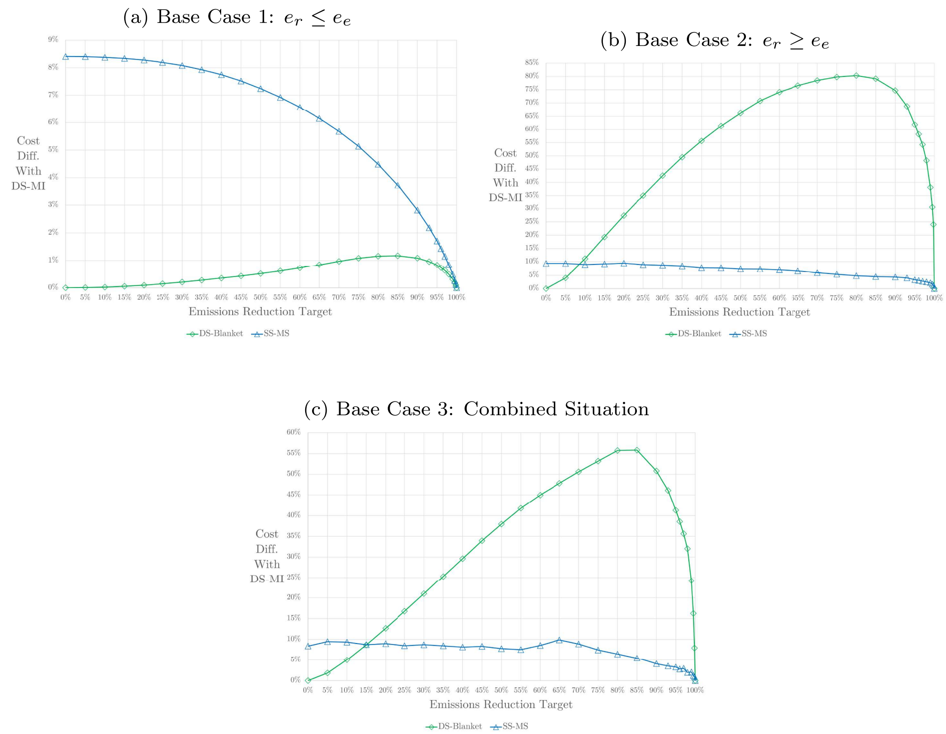
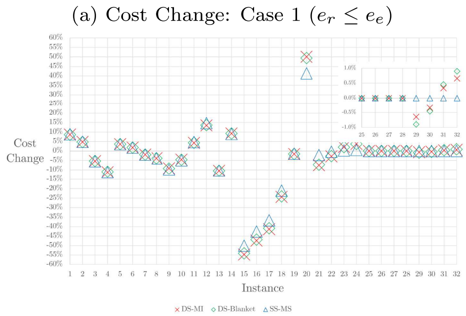
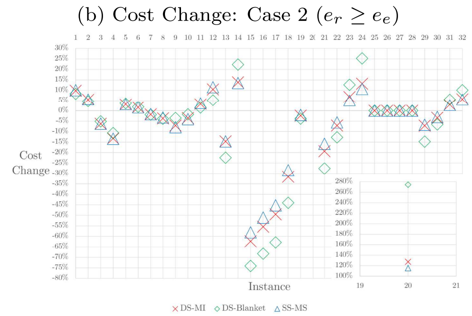


Figure 3: Difference in the optimal cost of benchmark approaches with the dual-sourcing multi-item approach given the target on reducible emissions

impact is not to the same extent for all approaches. As Figure 5 shows the dual-sourcing multi-item approach outperforms the single-sourcing mode-selection over the increase of the demand variability due to the possibility of partitioning the total demand between the regular and expedited channels. From our numerical analysis, we know that the optimal policies of the single-sourcing mode-selection approach cannot change in CV_D under the emissions reduction constraint which gives rise to an increase in holding and backorder penalty costs, where the dual-sourcing multi-item approach allows most of the items to order more from the expedited channel which keeps the total cost increase less than that of the single-sourcing mode-selection. For instance while the cost differences for 50% emissions reduction target at $min \;\; CV_D = 0.2$ are 6.33% in case 1, 6.47% in case 2, and 6.86% in case 3, at $min \;\; CV_D = 0.45$ these differences heighten to 8.35%, 8.44%, and 9%, respectively, which





Legend

Instance	1	2	3	4	5	6	7	8	Red. Target
CV_{μ_d}	0.3	0.4	0.6	0.7					50%
$\rho_{\mu_d,h}$					-0.3	-0.4	-0.6	-0.7	50%
Instance	9	10	11	12	13	14	15	16	Red. Target
$min\ CV_D$	0.2	0.3	0.4	0.5					50%
l					2	4			50%
c_p							3	4	50%
Instance	17	18	19	20	21	22	23	24	Red. Target
c_p	5	9	19	99					50%
μ_x					0.2	0.2	0.3	0.4	50%
Instance	25	26	27	28					Red. Target
$diff$ scale	0.8	0.9	1.1	1.2					50%
Instance	29	30	31	32					Red. Target
$diff$ scale	0.8	0.9	1.1	1.2					base 50% amount

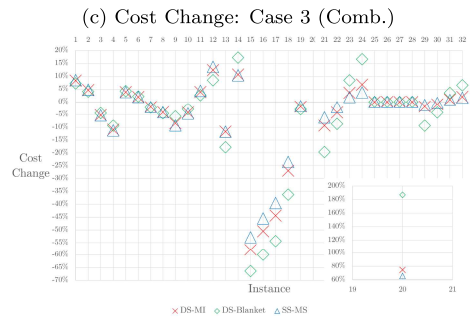
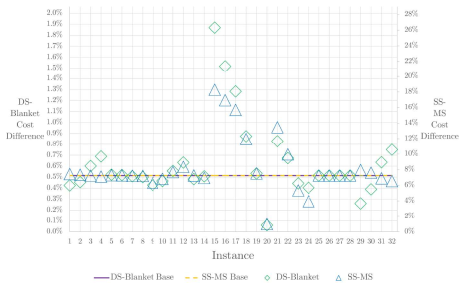


Figure 4: These graphs portray the impact of changing parameters on the optimal cost of the three approaches

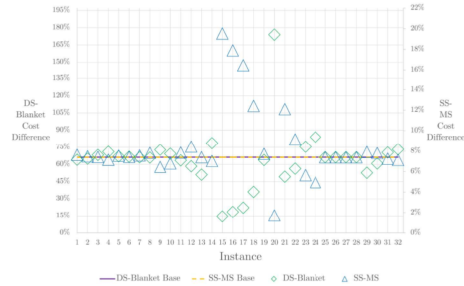
is significant. From Figures 4 and 5 (instances 13 and 14), it is evident that an enlarged lead time difference l has a greater effect on the blanket approach than the two multi-item approaches at a certain carbon reduction target because item-wise decision making restrains the flexibility of ordering cheaper items from the regular channel and more expensive ones from the expedited channel so that the target is achieved at a lower cost.

There is a widely held view among supply chain practitioners that dual-sourcing is more feasible in case a high service level is imperative. Instances 15 through 20 uncover that the gain of dual-sourcing multi-item approach over single-sourcing mode-selection surges at lower service levels. Figures 4 and 5, by way of illustration, depict that while at 95% service level the dual-sourcing multi-item approach surpasses single-sourcing mode-selection by 7.52% lower cost for case 1, 7.73% for case 2, and 8.08% for case 3, at 80% service level

(a) Cost Difference with DS-MI: Case 1 ($e_r \leq e_e$)



(b) Cost Difference with DS-MI: Case 2 ($e_r \geq e_e$)



Legend

Instance	1	2	3	4	5	6	7	8	Red. Target
CV_{μ_d}	0.3	0.4	0.6	0.7					50%
$\rho_{\mu_d,h}$					-0.3	-0.4	-0.6	-0.7	50%
Instance	9	10	11	12	13	14	15	16	Red. Target
$min\ CV_D$	0.2	0.3	0.4	0.5					50%
l					2	4			50%
c_p							3	4	50%
Instance	17	18	19	20	21	22	23	24	Red. Target
c_p	5	9	19	99					50%
μ_x					0.2	0.2	0.3	0.4	50%
Instance	25	26	27	28					Red. Target
$diff$ scale	0.8	0.9	1.1	1.2					50%
Instance	29	30	31	32					Red. Target
$diff$ scale	0.8	0.9	1.1	1.2					base 50% amount

(c) Cost Difference with DS-MI: Case 3 (Comb.)

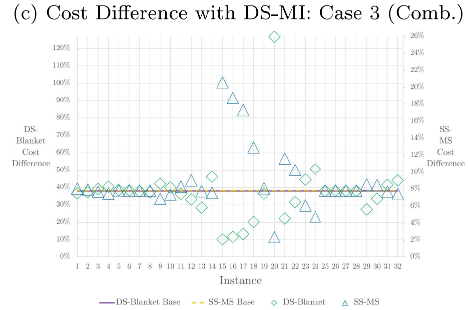


Figure 5: The change in the cost difference between approaches due to the parameters alteration are shown is these graphs

these surge to 16.94%, 17.90%, and 18.74%, respectively. Conversely, at higher service levels, the dual-sourcing multi-item method approaches the single-sourcing. The same relation is held in regards to the expedited acquisition cost c_e (instances 21 through 24), wherein the lower the c_e the more feasible the dual-sourcing approaches, specifically, the multi-item one. The reason for these phenomena is that at a higher c_e, which happens with the higher service level, too, the dual-sourcing approaches tend to order more from the cheaper regular suppliers so that with no emissions constraint at a very high c_e situation their optimal policies are almost equivalent to single-sourcing from the regular supplier. While, in cases 2 and 3 the dual-sourcing multi-item approach does so for most of the items, taking advantage of sourcing the others with lower emissions reduction cost from the expedited supplier, the dual-sourcing blanket approach does not have such a capability due to the itemized emissions reduction nature.

Finally, as long as the emissions of the least polluting modes remain constant, scaling the absolute emissions difference with a common scale factor does not change the solutions (cases 25 through 28 in Figures 4 and 5). However, scaling the absolute difference alters the solutions subject to a fixed absolute emissions amount (cases 29 through 32). In other words, such a scaling merely adjusts the absolute emissions, proportionally, and does not lead to an alteration in the solutions.

6. Concluding remarks

In this study, we introduced the dual-sourcing multi-item approach for making the most cost-effective and environmentally-friendly inventory decisions for a system with two suppliers, a regular one and a faster, yet more expensive expedited one. We analyzed the performance of this decision-making method through a comparison with another two leading approaches from the literature, namely the dual-sourcing blanket and the single-sourcing mode-selection. In order to do this we designed and performed wide-ranging numerical experiments to investigate the relative cost performance of these approaches in the presence of certain emissions reduction targets. We leveraged real-world carbon emissions data from apparel and auto industries to set up our experiments.

To calculate the optimal policies of the dual-sourcing multi-item approach, which is a special case of the NP-hard knapsack problem, we formulated the column generation algorithm whereby the master problem solutions are enhanced through computation of the decomposed sub-problems, recursively. Although in our numerical analysis we only utilized the DIP heuristic, the same solution strategies can be employed if multiple heuristics are considered for each item.

With our numerical experiments, we demonstrated that our dual-sourcing multi-item approach outperforms the single-sourcing significantly under the same carbon reduction targets. This significant advantage of dual-sourcing over single-sourcing methods remains even under high carbon reduction targets. However, we clarified that in many circumstances item-wise application of dual-sourcing such as the blanket approach generates worse results than wiser single-sourcing mode-selection which allows the flexibility of reducing cheaper carbon reduction, first. This aspect is more momentous when we have items with a more polluting regular channel in comparison with the expedited one.

Additionally, through a comprehensive parametric analysis, we examined the influence of different parameters on the performance of each approach individually and also relative to the others. As a result, it was illustrated that since the demand mean and holding cost are usually negatively correlated, increasing (decreasing) the volatility in demand mean or the correlation coefficient decreases (increases) the cost of each approach by the same order. Therefore, their relative cost does not change significantly. Furthermore, we indicated that using the multi-item approach (either dual-sourcing or single-sourcing) is more advantageous than the blanket approach when the difference between regular and expedited lead times l grows. The dual-sourcing multi-item approach was demonstrated to be more efficient than single-sourcing mode-selection at higher demand variability and lower service levels, yet the higher the service level the closer the dual-sourcing multi-item solutions to the single-sourcing ones as both of them tend to order more from the cheaper regular channel and compensate the excess emissions from the items with cheaper carbon reduction capacity. This happens with a higher expedited acquisition cost, as well. We also showed that the scaling of the emissions' absolute difference solely adjusts the emissions' amounts and does not have any influence on the solutions.

To further expand this research we propose these areas: a) A multi echelon system with multiple storage location,b) More complicated carbon emissions models, such as when use of less than truck load, c) A system with more than two suppliers, d) Taking advantage of more efficient dual-sourcing heuristics e.g. the PEIP.

Appendix A. Numerical Results - Base Cases

Table A.1: The results of the base case 1

Row	Emissions Reduction (%)	Emissions Target	DS-MI		DS-Blanket		SS-MS		Cost Increase Comparing DS-MI (%)		Emissions Deviation (%)		
			Cost	Emission	Cost	Emission	Cost	Emission	DS-Blanket	SS-MS	DS-MI	DS-Blanket	SS-MS
1	0%	6,345	52,039	6,345	52,039	6,345	56,415	3,747	0.00%	8.41%	0.00%	0.00%	-40.95%
2	5%	6,215	52,043	6,215	52,046	6,208	56,415	3,747	0.01%	8.40%	0.00%	-0.11%	-39.71%
3	10%	6,085	52,055	6,085	52,066	6,079	56,415	3,747	0.02%	8.38%	0.00%	-0.11%	-38.43%
4	15%	5,956	52,073	5,956	52,101	5,949	56,415	3,747	0.05%	8.34%	0.00%	-0.11%	-37.08%
5	20%	5,826	52,102	5,826	52,150	5,820	56,415	3,747	0.09%	8.28%	0.00%	-0.10%	-35.68%
6	25%	5,696	52,142	5,696	52,218	5,690	56,415	3,747	0.15%	8.19%	0.00%	-0.11%	-34.21%
7	30%	5,566	52,197	5,566	52,305	5,560	56,415	3,747	0.21%	8.08%	0.00%	-0.10%	-32.68%
8	35%	5,436	52,269	5,436	52,413	5,431	56,415	3,747	0.27%	7.93%	0.00%	-0.09%	-31.07%
9	40%	5,306	52,357	5,306	52,540	5,301	56,415	3,747	0.35%	7.75%	0.00%	-0.09%	-29.38%
10	45%	5,176	52,469	5,176	52,693	5,172	56,415	3,747	0.43%	7.52%	0.00%	-0.08%	-27.61%
11	50%	5,046	52,604	5,046	52,874	5,042	56,415	3,747	0.51%	7.25%	0.00%	-0.09%	-25.75%
12	55%	4,916	52,761	4,916	53,083	4,912	56,415	3,747	0.61%	6.93%	0.00%	-0.08%	-23.78%
13	60%	4,786	52,941	4,786	53,323	4,782	56,415	3,747	0.72%	6.56%	0.00%	-0.09%	-21.71%
14	65%	4,656	53,148	4,656	53,596	4,653	56,415	3,747	0.84%	6.15%	0.00%	-0.08%	-19.53%
15	70%	4,526	53,382	4,526	53,899	4,524	56,415	3,747	0.97%	5.68%	0.00%	-0.06%	-17.22%
16	75%	4,397	53,659	4,397	54,241	4,394	56,415	3,747	1.08%	5.14%	0.00%	-0.06%	-14.77%
17	80%	4,267	53,994	4,267	54,620	4,264	56,415	3,747	1.16%	4.49%	0.00%	-0.05%	-12.18%
18	85%	4,137	54,391	4,137	55,028	4,135	56,415	3,747	1.17%	3.72%	0.00%	-0.05%	-9.42%
19	90%	4,007	54,869	4,007	55,466	4,005	56,415	3,747	1.09%	2.82%	0.00%	-0.05%	-6.48%
20	93%	3,929	55,210	3,929	55,741	3,927	56,415	3,747	0.96%	2.18%	0.00%	-0.04%	-4.63%
21	95%	3,877	55,468	3,877	55,930	3,876	56,415	3,747	0.83%	1.71%	0.00%	-0.03%	-3.35%
22	96%	3,851	55,619	3,851	56,026	3,850	56,415	3,747	0.73%	1.43%	0.00%	-0.03%	-2.70%
23	97%	3,825	55,772	3,825	56,122	3,824	56,415	3,747	0.63%	1.15%	0.00%	-0.04%	-2.04%
24	98%	3,799	55,945	3,799	56,221	3,798	56,415	3,747	0.49%	0.84%	0.00%	-0.04%	-1.37%
25	99%	3,773	56,143	3,773	56,319	3,772	56,415	3,747	0.31%	0.48%	0.00%	-0.03%	-0.69%
26	99.5%	3,760	56,267	3,760	56,370	3,759	56,415	3,747	0.18%	0.26%	0.00%	-0.03%	-0.35%
27	99.8%	3,752	56,347	3,752	56,400	3,751	56,415	3,747	0.09%	0.12%	0.00%	-0.03%	-0.14%
28	100%	3,747	56,415	3,747	56,415	3,747	56,415	3,747	0.00%	0.00%	0.00%	0.00%	0.00%

Table A.2: The results of the base case 2

Row	Emissions Reduction (%)	Emissions Target	DS-MI		DS-Blanket		SS-MS		Cost Increase Comparing DS-MI (%)		Emissions Deviation (%)		
			Cost	Emission	Cost	Emission	Cost	Emission	DS-Blanket	SS-MS	DS-MI	DS-Blanket	SS-MS
1	0%	19,660	52,039	19,660	52,039	19,660	56,921	19,611	0.00%	9.38%	0.00%	0.00%	-0.25%
2	5%	19,218	52,378	19,218	54,479	19,216	57,281	19,081	4.01%	9.36%	0.00%	-0.01%	-0.71%
3	10%	18,777	52,916	18,777	58,810	18,773	57,632	18,768	11.14%	8.91%	0.00%	-0.02%	-0.05%
4	15%	18,336	53,531	18,336	63,867	18,331	58,447	18,296	19.31%	9.18%	0.00%	-0.02%	-0.22%
5	20%	17,894	54,460	17,894	69,368	17,889	59,613	17,857	27.38%	9.46%	0.00%	-0.03%	-0.21%
6	25%	17,453	55,619	17,453	75,094	17,447	60,573	17,405	35.01%	8.91%	0.00%	-0.03%	-0.28%
7	30%	17,012	56,841	17,012	81,030	17,004	61,793	17,006	42.55%	8.71%	0.00%	-0.04%	-0.03%
8	35%	16,570	58,268	16,570	87,105	16,562	63,178	16,563	49.49%	8.43%	0.00%	-0.05%	-0.05%
9	40%	16,129	59,888	16,129	93,249	16,121	64,568	16,115	55.71%	7.82%	0.00%	-0.05%	-0.09%
10	45%	15,688	61,673	15,688	99,524	15,679	66,443	15,676	61.37%	7.73%	0.00%	-0.05%	-0.08%
11	50%	15,246	63,638	15,246	105,824	15,236	68,342	15,234	66.29%	7.39%	0.00%	-0.06%	-0.08%
12	55%	14,805	65,703	14,805	112,209	14,794	70,501	14,787	70.78%	7.30%	0.00%	-0.08%	-0.12%
13	60%	14,364	68,127	14,364	118,593	14,354	72,922	14,356	74.07%	7.04%	0.00%	-0.07%	-0.06%
14	65%	13,922	70,848	13,922	125,051	13,912	75,539	13,918	76.51%	6.62%	0.00%	-0.07%	-0.03%
15	70%	13,481	73,724	13,481	131,565	13,467	78,115	13,480	78.46%	5.96%	0.00%	-0.10%	-0.01%
16	75%	13,040	76,769	13,040	138,007	13,026	80,921	13,029	79.77%	5.41%	0.00%	-0.11%	-0.08%
17	80%	12,598	80,147	12,598	144,526	12,584	84,027	12,592	80.33%	4.84%	0.00%	-0.12%	-0.05%
18	85%	12,157	84,352	12,157	151,103	12,140	88,140	12,156	79.14%	4.49%	0.00%	-0.14%	0.00%
19	90%	11,716	90,212	11,716	157,595	11,703	94,133	11,709	74.70%	4.35%	0.00%	-0.11%	-0.06%
20	93%	11,451	95,729	11,451	161,543	11,438	99,579	11,448	68.75%	4.02%	0.00%	-0.11%	-0.02%
21	95%	11,274	101,436	11,274	164,206	11,257	104,783	11,274	61.88%	3.30%	0.00%	-0.15%	0.00%
22	96%	11,186	104,574	11,186	165,499	11,171	107,810	11,182	58.26%	3.10%	0.00%	-0.13%	-0.03%
23	97%	11,098	108,115	11,098	166,805	11,079	111,101	11,098	54.28%	2.76%	0.00%	-0.17%	0.00%
24	98%	11,009	113,411	11,009	168,131	10,993	116,243	11,007	48.25%	2.50%	0.00%	-0.15%	-0.02%
25	99%	10,921	122,683	10,921	169,413	10,908	125,367	10,921	38.09%	2.19%	0.00%	-0.12%	0.00%
26	99.5%	10,877	130,308	10,877	170,074	10,862	132,464	10,876	30.52%	1.65%	0.00%	-0.14%	-0.01%
27	99.8%	10,850	137,420	10,850	170,451	10,836	139,052	10,850	24.04%	1.19%	0.00%	-0.14%	0.00%
28	100%	10,833	170,485	10,833	170,485	10,833	170,485	10,833	0.00%	0.00%	0.00%	0.00%	0.00%

Table A.3: The results of the base case 3

Row	Emissions Reduction (%)	Emissions Target	DS-MI		DS-Blanket		SS-MS		Cost Increase Comparing DS-MI (%)		Emissions Deviation (%)		
			Cost	Emission	Cost	Emission	Cost	Emission	DS-Blanket	SS-MS	DS-MI	DS-Blanket	SS-MS
1	0%	35,486	52,039	35,486	52,039	35,486	56,415	35,445	0.00%	8.41%	0.00%	0.00%	-0.12%
2	5%	34,163	52,173	34,163	53,131	34,154	57,126	32,997	1.84%	9.49%	0.00%	-0.03%	-3.42%
3	10%	32,841	52,432	32,841	55,062	32,829	57,344	31,115	5.02%	9.37%	0.00%	-0.04%	-5.26%
4	15%	31,518	52,733	31,518	57,311	31,504	57,344	31,115	8.68%	8.74%	0.00%	-0.04%	-1.28%
5	20%	30,195	53,052	30,195	59,768	30,178	57,829	30,011	12.66%	9.00%	0.00%	-0.06%	-0.61%
6	25%	28,873	53,381	28,873	62,333	28,853	57,926	28,320	16.77%	8.51%	0.00%	-0.07%	-1.91%
7	30%	27,550	53,716	27,550	64,995	27,524	58,411	27,217	21.00%	8.74%	0.00%	-0.09%	-1.21%
8	35%	26,227	54,054	26,227	67,718	26,209	58,636	25,872	25.28%	8.48%	0.00%	-0.07%	-1.36%
9	40%	24,905	54,403	24,904	70,496	24,883	58,854	23,989	29.58%	8.18%	0.00%	-0.09%	-3.67%
10	45%	23,582	54,763	23,582	73,350	23,558	59,339	22,886	33.94%	8.36%	0.00%	-0.10%	-2.95%
11	50%	22,259	55,250	22,259	76,214	22,234	59,564	21,541	37.94%	7.81%	0.00%	-0.11%	-3.23%
12	55%	20,936	55,834	20,936	79,150	20,910	60,050	20,438	41.76%	7.55%	0.00%	-0.13%	-2.38%
13	60%	19,614	56,648	19,614	82,105	19,582	61,502	19,595	44.94%	8.57%	0.00%	-0.16%	-0.10%
14	65%	18,291	57,562	18,291	85,082	18,271	63,261	17,374	47.81%	9.90%	0.00%	-0.11%	-5.01%
15	70%	16,968	58,535	16,968	88,144	16,925	63,747	16,271	50.58%	8.90%	0.00%	-0.25%	-4.11%
16	75%	15,646	59,524	15,646	91,165	15,608	63,971	14,925	53.16%	7.47%	0.00%	-0.24%	-4.60%
17	80%	14,323	60,521	14,323	94,240	14,294	64,457	13,822	55.71%	6.50%	0.00%	-0.20%	-3.50%
18	85%	13,000	62,483	13,000	97,361	12,961	65,909	12,980	55.82%	5.48%	0.00%	-0.30%	-0.16%
19	90%	11,677	66,621	11,677	100,455	11,653	69,326	11,675	50.79%	4.06%	0.00%	-0.21%	-0.02%
20	93%	10,884	70,060	10,884	102,358	10,838	72,522	10,872	46.10%	3.51%	0.00%	-0.42%	-0.11%
21	95%	10,355	73,343	10,355	103,626	10,323	75,757	10,336	41.29%	3.29%	0.00%	-0.31%	-0.19%
22	96%	10,090	75,233	10,090	104,254	10,058	77,322	10,082	38.57%	2.78%	0.00%	-0.32%	-0.08%
23	97%	9,826	77,336	9,826	104,880	9,797	79,617	9,797	35.62%	2.95%	0.00%	-0.29%	-0.29%
24	98%	9,561	79,924	9,561	105,518	9,531	81,483	9,555	32.02%	1.95%	0.00%	-0.32%	-0.07%
25	99%	9,297	85,470	9,297	106,136	9,277	87,228	9,285	24.18%	2.06%	0.00%	-0.21%	-0.13%
26	99.5%	9,164	91,568	9,164	106,449	9,133	92,688	9,160	16.25%	1.22%	0.00%	-0.34%	-0.05%
27	99.8%	9,085	98758.46	9,085	106621.2	9059.656	99,660	9,083	7.96%	0.91%	0.00%	-0.28%	-0.02%
28	100%	9,032	106654.4	9,032	106654.4	9032.071	106,654	9,032	0.00%	0.00%	0.00%	0.00%	0.00%

Appendix B. Numerical Results - Parametric Analysis

Table B.1: The results of the parametric analysis case 1

Row	Changed Parameter	Changed Value	Reduction Target	Absolute Costs						Cost Change Relative to the Approach's Base			Cost Change Relative to DS-MI			
				DS-MI		DS-Blanket		SS-MS					DS-Blanket		SS-MS	
				Base	New	Base	New	Base	New	DS-MI	DS-Blanket	SS-MS	Base	New	Base	New
1	CV_{μ_D}	0.3	50%	52,604	57,155	52,874	57,398	56,415	61,400	8.65%	8.56%	8.84%	0.51%	0.43%	7.25%	7.43%
2	CV_{μ_D}	0.4	50%	52,604	55,130	52,874	55,381	56,415	59,180	4.80%	4.74%	4.90%	0.51%	0.45%	7.25%	7.35%
3	CV_{μ_D}	0.6	50%	52,604	49,781	52,874	50,080	56,415	53,374	-5.37%	-5.28%	-5.39%	0.51%	0.60%	7.25%	7.22%
4	CV_{μ_D}	0.7	50%	52,604	46,734	52,874	47,055	56,415	50,055	-11.16%	-11.00%	-11.27%	0.51%	0.69%	7.25%	7.11%
5	$\rho_{\mu_d,h}$	-0.3	50%	52,604	54,489	52,874	54,773	56,415	58,463	3.58%	3.59%	3.63%	0.51%	0.52%	7.25%	7.29%
6	$\rho_{\mu_d,h}$	-0.4	50%	52,604	53,560	52,874	53,838	56,415	57,453	1.82%	1.82%	1.84%	0.51%	0.52%	7.25%	7.27%
7	$\rho_{\mu_d,h}$	-0.6	50%	52,604	51,617	52,874	51,879	56,415	55,346	-1.88%	-1.88%	-1.90%	0.51%	0.51%	7.25%	7.22%
8	$\rho_{\mu_d,h}$	-0.7	50%	52,604	50,593	52,874	50,846	56,415	54,237	-3.82%	-3.84%	-3.86%	0.51%	0.50%	7.25%	7.20%
9	$min\ CV_D$	0.2	50%	52,604	47,796	52,874	48,000	56,415	50,821	-9.14%	-9.22%	-9.92%	0.51%	0.43%	7.25%	6.33%
10	$min\ CV_D$	0.25	50%	52,604	50,212	52,874	50,446	56,415	53,633	-4.55%	-4.59%	-4.93%	0.51%	0.46%	7.25%	6.81%
11	$min\ CV_D$	0.35	50%	52,604	54,857	52,874	55,162	56,415	59,075	4.28%	4.33%	4.71%	0.51%	0.56%	7.25%	7.69%
12	$min\ CV_D$	0.45	50%	52,604	59,707	52,874	60,085	56,415	64,695	13.50%	13.64%	14.68%	0.51%	0.63%	7.25%	8.35%
13	l	2	50%	52,604	47,127	52,874	47,354	56,415	50,547	-10.41%	-10.44%	-10.40%	0.51%	0.48%	7.25%	7.26%
14	l	4	50%	52,604	57,482	52,874	57,774	56,415	61,469	9.27%	9.27%	8.96%	0.51%	0.51%	7.25%	6.94%
15	c_p	3	50%	52,604	23,804	52,874	24,249	56,415	28,152	-54.75%	-54.14%	-50.10%	0.51%	1.87%	7.25%	18.27%
16	c_p	4	50%	52,604	27,684	52,874	28,105	56,415	32,373	-47.37%	-46.85%	-42.62%	0.51%	1.52%	7.25%	16.94%
17	c_p	5	50%	52,604	30,863	52,874	31,259	56,415	35,706	-41.33%	-40.88%	-36.71%	0.51%	1.28%	7.25%	15.69%
18	c_p	9	50%	52,604	39,781	52,874	40,128	56,415	44,531	-24.38%	-24.11%	-21.07%	0.51%	0.87%	7.25%	11.94%
19	c_p	19	50%	52,604	51,768	52,874	52,044	56,415	55,659	-1.59%	-1.57%	-1.34%	0.51%	0.53%	7.25%	7.52%
20	c_p	99	50%	52,604	78,945	52,874	78,993	56,415	79,730	50.08%	49.40%	41.33%	0.51%	0.06%	7.25%	0.99%
21	μ_x	0.15	50%	52,604	48,673	52,874	49,077	56,415	55,223	-7.47%	-7.18%	-2.11%	0.51%	0.83%	7.25%	13.46%
22	μ_x	0.2	50%	52,604	51,109	52,874	51,453	56,415	56,200	-2.84%	-2.69%	-0.38%	0.51%	0.67%	7.25%	9.96%
23	μ_x	0.3	50%	52,604	53,712	52,874	53,951	56,415	56,577	2.11%	2.04%	0.29%	0.51%	0.44%	7.25%	5.33%
24	μ_x	0.35	50%	52,604	54,585	52,874	54,805	56,415	56,739	3.77%	3.65%	0.57%	0.51%	0.40%	7.25%	3.95%
25	$diff$ scale	0.8	50%	52,604	52,604	52,874	52,874	56,415	56,415	0.00%	0.00%	0.00%	0.51%	0.51%	7.25%	7.25%
26	$diff$ scale	0.9	50%	52,604	52,604	52,874	52,874	56,415	56,415	0.00%	0.00%	0.00%	0.51%	0.51%	7.25%	7.25%
27	$diff$ scale	1.1	50%	52,604	52,604	52,874	52,874	56,415	56,415	0.00%	0.00%	0.00%	0.51%	0.51%	7.25%	7.25%
28	$diff$ scale	1.2	50%	52,604	52,604	52,874	52,874	56,415	56,415	0.00%	0.00%	0.00%	0.51%	0.51%	7.25%	7.25%
29	$diff$ scale	0.8	Base 50% Amount	52,604	52,262	52,874	52,398	56,415	56,415	-0.65%	-0.90%	0.00%	0.51%	0.26%	7.25%	7.95%
30	$diff$ scale	0.9	Base 50% Amount	52,604	52,425	52,874	52,629	56,415	56,415	-0.34%	-0.46%	0.00%	0.51%	0.39%	7.25%	7.61%
31	$diff$ scale	1.1	Base 50% Amount	52,604	52,781	52,874	53,116	56,415	56,415	0.34%	0.46%	0.00%	0.51%	0.64%	7.25%	6.89%
32	$diff$ scale	1.2	Base 50% Amount	52,604	52,951	52,874	53,349	56,415	56,415	0.66%	0.90%	0.00%	0.51%	0.75%	7.25%	6.54%

Table B.2: The results of the parametric analysis case 2

Row	Changed Parameter	Changed Value	Reduction Target	Absolute Costs						Cost Change Relative to the Approach's Base			Cost Change Relative to DS-MI			
				DS-MI		DS-Blanket		SS-MS					DS-Blanket		SS-MS	
				Base	New	Base	New	Base	New	DS-MI	DS-Blanket	SS-MS	Base	New	Base	New
1	CV_{μ_D}	0.3	50%	63,638	69,889	105,824	114,685	68,342	75,227	9.82%	8.37%	10.07%	66.29%	64.10%	7.39%	7.64%
2	CV_{μ_D}	0.4	50%	63,638	67,127	105,824	110,725	68,342	72,154	5.48%	4.63%	5.58%	66.29%	64.95%	7.39%	7.49%
3	CV_{μ_D}	0.6	50%	63,638	59,662	105,824	100,391	68,342	64,088	-6.25%	-5.13%	-6.22%	66.29%	68.27%	7.39%	7.42%
4	CV_{μ_D}	0.7	50%	63,638	55,234	105,824	94,504	68,342	59,186	-13.21%	-10.70%	-13.40%	66.29%	71.10%	7.39%	7.16%
5	$\rho_{\mu_d,h}$	-0.3	50%	63,638	65,638	105,824	109,651	68,342	70,588	3.14%	3.62%	3.29%	66.29%	67.05%	7.39%	7.54%
6	$\rho_{\mu_d,h}$	-0.4	50%	63,638	64,666	105,824	107,768	68,342	69,466	1.62%	1.84%	1.64%	66.29%	66.65%	7.39%	7.42%
7	$\rho_{\mu_d,h}$	-0.6	50%	63,638	62,492	105,824	103,817	68,342	67,221	-1.80%	-1.90%	-1.64%	66.29%	66.13%	7.39%	7.57%
8	$\rho_{\mu_d,h}$	-0.7	50%	63,638	61,309	105,824	101,735	68,342	66,107	-3.66%	-3.86%	-3.27%	66.29%	65.94%	7.39%	7.83%
9	$min\ CV_D$	0.2	50%	63,638	59,127	105,824	102,143	68,342	62,951	-7.09%	-3.48%	-7.89%	66.29%	72.75%	7.39%	6.47%
10	$min\ CV_D$	0.25	50%	63,638	61,397	105,824	103,961	68,342	65,573	-3.52%	-1.76%	-4.05%	66.29%	69.33%	7.39%	6.80%
11	$min\ CV_D$	0.35	50%	63,638	65,719	105,824	107,464	68,342	70,881	3.27%	1.55%	3.72%	66.29%	63.52%	7.39%	7.86%
12	$min\ CV_D$	0.45	50%	63,638	70,266	105,824	111,270	68,342	76,196	10.42%	5.15%	11.49%	66.29%	58.36%	7.39%	8.44%
13	l	2	50%	63,638	54,313	105,824	82,058	68,342	58,330	-14.65%	-22.46%	-14.65%	66.29%	51.08%	7.39%	7.40%
14	l	4	50%	63,638	72,453	105,824	129,446	68,342	77,551	13.85%	22.32%	13.48%	66.29%	78.66%	7.39%	7.04%
15	c_p	3	50%	63,638	23,950	105,824	27,423	68,342	28,628	-62.36%	-74.09%	-58.11%	66.29%	14.50%	7.39%	19.53%
16	c_p	4	50%	63,638	28,378	105,824	33,620	68,342	33,457	-55.41%	-68.23%	-51.05%	66.29%	18.47%	7.39%	17.90%
17	c_p	5	50%	63,638	32,140	105,824	39,286	68,342	37,427	-49.50%	-62.88%	-45.24%	66.29%	22.23%	7.39%	16.45%
18	c_p	9	50%	63,638	43,537	105,824	59,207	68,342	48,941	-31.59%	-44.05%	-28.39%	66.29%	35.99%	7.39%	12.41%
19	c_p	19	50%	63,638	62,125	105,824	101,806	68,342	66,930	-2.38%	-3.80%	-2.07%	66.29%	63.87%	7.39%	7.73%
20	c_p	99	50%	63,638	144,543	105,824	396,039	68,342	147,041	127.13%	274.24%	115.15%	66.29%	173.99%	7.39%	1.73%
21	μ_x	0.15	50%	63,638	51,335	105,824	76,646	68,342	57,543	-19.33%	-27.57%	-15.80%	66.29%	49.31%	7.39%	12.09%
22	μ_x	0.2	50%	63,638	59,100	105,824	92,359	68,342	64,504	-7.13%	-12.72%	-5.61%	66.29%	56.28%	7.39%	9.14%
23	μ_x	0.3	50%	63,638	67,943	105,824	119,207	68,342	71,783	6.77%	12.65%	5.03%	66.29%	75.45%	7.39%	5.65%
24	μ_x	0.35	50%	63,638	72,045	105,824	132,535	68,342	75,633	13.21%	25.24%	10.67%	66.29%	83.96%	7.39%	4.98%
25	$diff$ scale	0.8	50%	63,638	63,638	105,824	105,824	68,342	68,342	0.00%	0.00%	0.00%	66.29%	66.29%	7.39%	7.39%
26	$diff$ scale	0.9	50%	63,638	63,638	105,824	105,824	68,342	68,342	0.00%	0.00%	0.00%	66.29%	66.29%	7.39%	7.39%
27	$diff$ scale	1.1	50%	63,638	63,638	105,824	105,824	68,342	68,342	0.00%	0.00%	0.00%	66.29%	66.29%	7.39%	7.39%
28	$diff$ scale	1.2	50%	63,638	63,638	105,824	105,824	68,342	68,342	0.00%	0.00%	0.00%	66.29%	66.29%	7.39%	7.39%
29	$diff$ scale	0.8	Base 50% Amount	63,638	59,065	105,824	90,185	68,342	63,742	-7.19%	-14.78%	-6.73%	66.29%	52.69%	7.39%	7.92%
30	$diff$ scale	0.9	Base 50% Amount	63,638	61,463	105,824	98,853	68,342	66,258	-3.42%	-6.59%	-3.05%	66.29%	60.83%	7.39%	7.80%
31	$diff$ scale	1.1	Base 50% Amount	63,638	65,506	105,824	111,630	68,342	70,257	2.94%	5.49%	2.80%	66.29%	70.41%	7.39%	7.25%
32	$diff$ scale	1.2	Base 50% Amount	63,638	67,268	105,824	116,468	68,342	72,068	5.71%	10.06%	5.45%	66.29%	73.14%	7.39%	7.13%

Table B.3: The results of the parametric analysis case 3

Row	Changed Parameter	Changed Value	Reduction Target	Absolute Costs						Cost Change Relative to the Approach's Base			Cost Change Relative to DS-MI			
				DS-MI		DS-Blanket		SS-MS					DS-Blanket		SS-MS	
				Base	New	Base	New	Base	New	DS-MI	DS-Blanket	SS-MS	Base	New	Base	New
1	CV_{μ_D}	0.3	50%	55,250	59,860	76,214	81,744	59,564	64,664	8.35%	7.26%	8.56%	37.94%	36.56%	7.81%	8.03%
2	CV_{μ_D}	0.4	50%	55,250	57,820	76,214	79,320	59,564	62,417	4.65%	4.08%	4.79%	37.94%	37.18%	7.81%	7.95%
3	CV_{μ_D}	0.6	50%	55,250	52,349	76,214	72,820	59,564	56,375	-5.25%	-4.45%	-5.35%	37.94%	39.10%	7.81%	7.69%
4	CV_{μ_D}	0.7	50%	55,250	49,200	76,214	69,084	59,564	52,868	-10.95%	-9.36%	-11.24%	37.94%	40.41%	7.81%	7.46%
5	$\rho_{\mu_d,h}$	-0.3	50%	55,250	57,385	76,214	79,460	59,564	61,875	3.87%	4.26%	3.88%	37.94%	38.47%	7.81%	7.82%
6	$\rho_{\mu_d,h}$	-0.4	50%	55,250	56,332	76,214	77,865	59,564	60,732	1.96%	2.17%	1.96%	37.94%	38.22%	7.81%	7.81%
7	$\rho_{\mu_d,h}$	-0.6	50%	55,250	54,140	76,214	74,505	59,564	58,364	-2.01%	-2.24%	-2.01%	37.94%	37.62%	7.81%	7.80%
8	$\rho_{\mu_d,h}$	-0.7	50%	55,250	52,989	76,214	72,728	59,564	57,125	-4.09%	-4.57%	-4.09%	37.94%	37.25%	7.81%	7.81%
9	$min\ \ CV_D$	0.2	50%	55,250	50,589	76,214	71,848	59,564	54,060	-8.44%	-5.73%	-9.24%	37.94%	42.02%	7.81%	6.86%
10	$min\ \ CV_D$	0.25	50%	55,250	52,927	76,214	74,021	59,564	56,821	-4.20%	-2.88%	-4.60%	37.94%	39.86%	7.81%	7.36%
11	$min\ \ CV_D$	0.35	50%	55,250	57,420	76,214	78,245	59,564	62,178	3.93%	2.66%	4.39%	37.94%	36.27%	7.81%	8.28%
12	$min\ \ CV_D$	0.45	50%	55,250	62,121	76,214	82,691	59,564	67,713	12.44%	8.50%	13.68%	37.94%	33.11%	7.81%	9.00%
13	l	2	50%	55,250	48,801	76,214	62,658	59,564	52,578	-11.67%	-17.79%	-11.73%	37.94%	28.39%	7.81%	7.74%
14	l	4	50%	55,250	61,154	76,214	89,393	59,564	65,771	10.69%	17.29%	10.42%	37.94%	46.18%	7.81%	7.55%
15	c_p	3	50%	55,250	23,293	76,214	25,638	59,564	28,087	-57.84%	-66.36%	-52.85%	37.94%	10.07%	7.81%	20.58%
16	c_p	4	50%	55,250	27,345	76,214	30,530	59,564	32,469	-50.51%	-59.94%	-45.49%	37.94%	11.65%	7.81%	18.74%
17	c_p	5	50%	55,250	30,707	76,214	34,789	59,564	36,016	-44.42%	-54.35%	-39.53%	37.94%	13.29%	7.81%	17.29%
18	c_p	9	50%	55,250	40,367	76,214	48,543	59,564	45,575	-26.94%	-36.31%	-23.49%	37.94%	20.25%	7.81%	12.90%
19	c_p	19	50%	55,250	54,230	76,214	73,987	59,564	58,612	-1.84%	-2.92%	-1.60%	37.94%	36.43%	7.81%	8.08%
20	c_p	99	50%	55,250	96,469	76,214	218,669	59,564	98,721	74.61%	186.91%	65.74%	37.94%	126.67%	7.81%	2.33%
21	μ_x	0.15	50%	55,250	50,105	76,214	61,222	59,564	55,914	-9.31%	-19.67%	-6.13%	37.94%	22.19%	7.81%	11.60%
22	μ_x	0.2	50%	55,250	52,931	76,214	69,590	59,564	58,356	-4.20%	-8.69%	-2.03%	37.94%	31.47%	7.81%	10.25%
23	μ_x	0.3	50%	55,250	57,227	76,214	82,645	59,564	60,700	3.58%	8.44%	1.91%	37.94%	44.41%	7.81%	6.07%
24	μ_x	0.35	50%	55,250	59,003	76,214	88,898	59,564	61,828	6.79%	16.64%	3.80%	37.94%	50.67%	7.81%	4.79%
25	$diff$ scale	0.8	50%	55,250	55,250	76,214	76,214	59,564	59,564	0.00%	0.00%	0.00%	37.94%	37.94%	7.81%	7.81%
26	$diff$ scale	0.9	50%	55,250	55,250	76,214	76,214	59,564	59,564	0.00%	0.00%	0.00%	37.94%	37.94%	7.81%	7.81%
27	$diff$ scale	1.1	50%	55,250	55,250	76,214	76,214	59,564	59,564	0.00%	0.00%	0.00%	37.94%	37.94%	7.81%	7.81%
28	$diff$ scale	1.2	50%	55,250	55,250	76,214	76,214	59,564	59,564	0.00%	0.00%	0.00%	37.94%	37.94%	7.81%	7.81%
29	$diff$ scale	0.8	Base 50% Amount	55,250	54,217	76,214	69,075	59,564	58,854	-1.87%	-9.37%	-1.19%	37.94%	27.40%	7.81%	8.55%
30	$diff$ scale	0.9	Base 50% Amount	55,250	54,718	76,214	73,014	59,564	59,339	-0.96%	-4.20%	-0.38%	37.94%	33.44%	7.81%	8.45%
31	$diff$ scale	1.1	Base 50% Amount	55,250	55,775	76,214	78,924	59,564	60,050	0.95%	3.56%	0.82%	37.94%	41.50%	7.81%	7.66%
32	$diff$ scale	1.2	Base 50% Amount	55,250	56,374	76,214	81,188	59,564	60,554	2.04%	6.53%	1.66%	37.94%	44.02%	7.81%	7.41%