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Research Article

REFURBISHING SUPPLY CHAIN OPTIMIZATION UNDER CAP-AND-TRADE POLICY: A COMPARATIVE ANALYSIS OF DISTRIBUTION CHANNEL STRATEGIES

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Abstract
To advance the circular economy, refurbishing activities are essential to mitigate industrial waste. While cap-and-trade policies regulate greenhouse emissions, their mathematical interactions with refurbishing distribution strategies remain under-researched. This study assesses the implications of distribution structures on profitability under environmental constraints. Two multivariable optimization models were developed: Model C (direct distribution) and Model M (indirect distribution via a retailer). Objective functions were optimized for price and production volume under cap-and-trade constraints. A sensitivity analysis of 15 parameters employed partial derivatives to determine the profit function's rate of change relative to market potential (Q), price elasticity (λ), cannibalization (β), and carbon costs. Model C yielded a higher optimum value ($165,796) than Model M ($124,341). Sensitivity analysis identified Q as having the highest positive gradient. Conversely, profits exhibited high sensitivity to λ and β, where incremental coefficient increases led to non-linear margin deterioration. Mathematically, optimal pricing proved nearly inelastic to carbon price fluctuations, suggesting that production costs and demand coefficients dominate the profit function's Hessian matrix. Model C maintained lower pricing for new ($370,219) and refurbished items ($220,163) compared to Model M ($555,109 and $330,081). This study demonstrates that direct distribution mitigates “double marginalization” in multi-tier chains. Mathematically, firms should prioritize optimizing market parameters (λ, β) over carbon-cost mitigation. Furthermore, policymakers must recognize that cap-and-trade programs may drive industries toward vertical integration to achieve mathematical optimality.

Keywords: Cap-and-Trade Policy, Distribution Channel Optimization, Mathematical Modeling, Profit Maximization, Refurbishing Supply Chain.

INTRODUCTION

The global economy is currently confronted with unprecedented environmental challenges as a result of the traditional global economic model and its linear economic approach to production and disposal, as illustrated in the take-make-dispose approach (Dabo, Amajuoyi, & Alparslan, 2025). This has also led to massive amounts of electronic waste in the world, as highlighted in the Global E-waste Monitor report of 2020, which indicated the production of 53.6 million metric tons of e-waste in the world in 2019 and projected to rise to 74 million metric tons by the end of 2030. On the other hand, different industries are also causing carbon emissions into the atmosphere, as production activities in factories are noted to be responsible for around 20% of global CO^2 emissions (Agency International Energy, 2021).

The emergence of the circular economy model has thus come as a complete package, focusing entirely on the principles of reduce, reuse, recycle, and repair, aiming to create a cycle of products and packaging and, consequently, closing the loop effectively and avoiding unnecessary waste and harm to the environment (Foundation, 2015). Under the circular economy model, refurbishing can be seen as a vital practice accelerating the product lifetime and reducing the amount of waste and emissions generated during the manufacturing process (Cahyani & Kurdhi, 2025). Refurbishing involves restoring used products to pre-owned conditions through a series of processes including cleaning, repair, and replacement of worn-out components and parts and, subsequently, making the products available in the market at competitive prices (Abbey, Blackburn, & Guide, 2015). Prominent technology giants such as Apple, Samsung, and Dell have already proven the viability of refurbishing, yielding effective results from the environmental perspective as well. Research has indicated a refurbished smartphone market of 282.6 million units in the global market during the year 2022, revealing a growth of 11.5% over the year 2021 (Corporation, 2023).

Along with these developments in circular economy, different countries of the world are adopting carbon pricing models to combat global warming. For instance, countries of the European Union, California, China, etc., adopted cap and trade systems, in which limits are imposed on emissions, and trade of permits is allowed (world Bank, 2021). In such systems, economic incentives are developed to reduce emissions, along with allowing trading of permits (Zhang Y. , Zhang, Zhou, & Cheng, 2024). Integration of such cap and trade systems with the operations of the manufacturing enterprise would add further complexity to supply chain decisions or production operations (Zhang, Zhang, Hu, & Yang, 2025)

Despite this growing research on the operations of refurbishing and the implementation of carbon policy, important gaps persist regarding how both are optimized jointly. Past studies have modeled refurbishing supply chains in isolation (Ochinnikov, 2011) or examined capand-trade policies in isolation from product lifecycle decisions (Zhang & Xu, 2013). However, the interaction of environmental regulations with distribution channel choices in refurbishing supply chains remains unexplored (Cahyani & Kurdhi, 2025). The gap is all the more important inasmuch as distribution strategies have a fundamental impact on both profitability and carbon footprints (Wu, Miao, Zhang, Zou, & Shen, 2025)

This research contributes to the field of sustainable operations management in several ways. From a theoretical point of view, this research offers the first conjoint analysis of structure in the channel of distribution, refurbishing services, and a cap-and-trade policy, despite prior research examining these factors individually (Zhang Y. , Zhang, Zhou, & Cheng, 2024) From a methodological point of view, this research presents a mathematical modeling approach, optimizing the role of carbon trading within multi-echelon supply chain management, building upon refurbishing service research that fails to take environmental regulations into consideration (Wu, Miao, Zhang, Zou, & Shen, 2025). From a practical perspective, this study represents an insightful tool for Original Equipment Manufacturers (OEMs) operating in a market with limited resources, as they determine the distribution strategy of refurbished products On another level, these results may be seen as evidence of how regulations, such as those listed above, may affect the distribution strategies of firms, highlighting an unintentional effect of these regulations (Zhang Y. , Zhang, Zhou, & Cheng, 2024). By performing the sensitivity analysis, there is comprehensive understanding of the parameters so that their effects are seen with respect to different channel configurations. From the analysis, some parameters are observed to be dominant over others in their effect on profitability, be it in any kind of distribution structure (Pradana & Kurdhi, 2024).

In particular, the extant literature does not address the following important research questions: (1) How do cap-and-trade policies influence optimal pricing and production decisions in refurbishment supply chains with varying distributional structures? (2) What is the superior strategy of refurbishment supply chain structure: a direct OEM-to-consumer or indirect OEM-to-retailer-to-consumer strategy? (3)

What are the differential effects of significant market and environmental factors on various supply chain configurations?

Addressing these gaps is urgent, rooted both in practical industrial needs and requirements for theoretical advancement. Firms operating refurbishing programs under tightening environmental regulations require evidence-based guidance on how to make distribution strategy decisions (Zhang Y. , Zhang, Zhou, & Cheng, 2024) Policymakers must comprehend how supply chain structural decisions are affected by carbon pricing mechanisms when designing effective regulations that foster both environmental and economic objectives (Zhang Y. , Zhang, Hu, & Yang, 2025) Academically, the combination of refurbishing operations, carbon policy, and distribution channel theory contributes to the emerging field of sustainable operations management (Tiwari, 2026).

This research is focused on the development and comparison of different mathematical optimization models that represent refurbishing supply chains operating under cap-and-trade policies and with different distribution channel configurations. The specific objectives of this effort are:

1. To develop mathematical models of the refurbishing supply chains with the cap-and-trade constraints for direct distribution (Model C) and indirect distribution via retailers (Model M).
2. To find out the appropriate price and production quantity to maximize profitability within all configurations of distribution channels based on carbon emission constraints.
3. To compare the economic performance of direct and indirect distribution channels in refurbishing supply chains with different sellers under cap-and-trade regulations through case studies (Cahyani & Kurdhi, 2025)
4. To perform the sensitivity analysis of optimal solutions with respect to key market parameters such as market potential, price elasticity, cannibalization coefficient; and environmental parameters such as carbon price, and emission rates (Zhang Y. , Zhang, Hu, & Yang, 2025)
5. To provide managerial insights and policy implications for the environmental regulations on sustainable supply chain design (Tiwari, 2026)

RESEARCH METHOD

This study uses a quantitative research methodology based on mathematical modeling and optimization techniques. The research design being analytical and comparative brings out theoretical models that represent realistic refurbishing supply chain operations under cap-and-trade regulations (Zhang, Zhang, Hu, & Yang, 2025). We take a deductive approach by constructing mathematical frameworks based on established economic and operations management theories, then analytically deriving the optimal solutions (Zhang, Zhang, Zhou, & Cheng, 2024).

The five stages involve model formulation, based on the given supply chain structure and carbon policy constraints; the derivation of the analytical solution, applying multivariable calculus and optimization theory; numerical implementation using the values of parameters from the literature survey; comparative analysis for the performance comparison of two different configurations in a distribution channel (Cahyani & Kurdhi, 2025); and sensitivity analysis with respect to changes in key parameters (Zhang Y. , Zhang, Zhou, & Cheng, 2024). Since this research applies mathematical modeling rather than data collection from the field, the traditional sampling technique is not applicable. Instead, we use the values of parameters from existing literature in refurbishing operations and the carbon market in order to ensure model validity and practical relevance. The selection of the parameters is based on the purposive sampling logic, wherein values are selected that can best represent realistic market conditions as evidenced by previous empirical studies (Pradana & Kurdhi, 2024).

We used base parameter values from existing peerreviewed studies: for example, Ovchinnikov 2011 on refurbishing cost structures, Zhang & Xu 2013 on cap-and-trade market parameters, and Kurdhi et al. 2023 on demand function coefficients in refurbishing markets. This approach ensures our models reflect the empirically observed dynamics of markets, while maintaining theoretical generalizability (Cahyani & Kurdhi, 2025). While data collection is a systematic study of values for parameters from published data, it consists of the following steps:

1. Literature identification: Extensive literature search from the Web of Science, Scopus, Google Scholar databases from the year 2010-2024 regarding refurbish, cap and trade, and channel distributions (Tiwari, 2026)
2. Parameter extraction: Systematic recording of numerical values of market potentials, price elasticity, cost parameters, carbon emission factors, and carbon prices from chosen studies (Zhang Y. , Zhang, Zhou, & Cheng, 2024)

3. Data validation: Verifying information by cross-referencing parameter values from various sources.
4. Range determination: defining appropriate parameter ranges for sensitivity analysis based on observed variability in the existing empirical literature.

Table 1 below represents the entire data collection tool comprising definitions of parameters, measurement units, references, and baseline values.

Table 1. Data Collection Instrument and Parameter Sources

Parameter	Definition	Unit	Base Value	Source
Q	Market potential for new products	Units	500,000	Kurdhi et al. (2023)
k	Price elasticity of new products	Units/$	0.5	Ovchinnikov (2011)
pc	Carbon emission price	\$/ton CO_2	50	Zhang & Xu (2013)

The main research instruments in this context are the mathematical optimization models developed for this study. These will act as internal analytical tools that deduce the optimum decisions and compare performances of different distribution channels (Cahyani & Kurdhi, 2025)The supporting computational tools are:

1. Mathematical modeling framework: A system of equations displayed profit functions, demand functions, cost structures, and cap-and-trade constraints for both distribution channels.
2. Optimisation Solver: Derivation of FOCs with Analytics and numerical computation software to solve systems of equations.
3. Sensitivity analysis toolkit: Computational procedures for systematic variation of parameter values and tracking of impacts on optimal solutions.
4. Visualization software: Graphical representation tools of sensitivity analysis results and performance of various models.

Similar to empirical studies where power analysis is necessary as a means of determining the sample size, in a mathematical optimization approach, analytical solutions are used; they are deterministic depending on the model and parameters used. The power of the current study lies in its analytical precision and the comprehensiveness of the parameters used rather than the outcome's statistical significance (Pradana & Kurdhi, 2024). The strength of the present study, from an analytical viewpoint, stems from the fact that it undertakes a complete optimization to ensure global optimality under specified assumption sets, follows a comparative analysis of two different distribution structures (Cahyani & Kurdhi, 2025), undertakes a sensitivity study with respect to 15 parameters including systematic variation (±20 percent from baseline) to derive 150 scenario comparisons, and rests upon parameter sets that have been substantiated in the empirical literature (Zhang, Zhang, Zhou, & Cheng, 2024). Sensitivity analysis, which tests different parameters individually and collectively, has also shown to be very comprehensive, ensuring that our conclusions were well supported. This increases confidence in our ability to extrapolate our findings to values not specifically covered in our baseline case (Zhang, Zhang, Hu, & Yang, 2025).

There are two models: the refurbishing model with the effect of cap-and-trade policy with direct distribution, namely OEMs, and the refurbishing model with the effect of cap-and-trade policy with indirect distribution, namely OEMs and retailers. The following are the assumptions required in formulating the profit function.

Assumption 1. *Both parties involved, the OEM and the retailer maximize the profit function in the single-period model* (Zhang, Zhang, Hu, & Yang, 2025).

Assumption 2. *There are two market segmentations based on the price offered, namely high-end customers and low-end customers* (Pradana & Kurdhi, 2024).

The existence of refurbished products causes some high-end customers to switch to refurbished products. $\alpha(p_r)$ is a cannibalization function with value $\alpha(p_r) = b(p_n - p_r)$ where α is the proportion of high-end customers who move from new products to refurbished products, and $\alpha(p_r) \in [0,1]$. This results in $Q - b(p_n - p_r)$ number of high-end customers who continue to buy the new product with Q being the market potential of the new product, b being the cannibalization coefficient with $b \geq 0$, p_n

being the price of the new product, and p_r being the price of the refurbished product (Cahyani & Kurdhi, 2025).

Assumption 3. *The production cost of a refurbished product is always lower than the production cost of a new product* $(c_r < c_n)$ (Pradana & Kurdhi, 2024).

Assumption 4. *Carbon emissions resulting from manufacturing refurbished products are lower than carbon emissions resulting from manufacturing new products* $(e_r < e_n)$ (Wu, Miao, Zhang, Zou, & Shen, 2025).

Assumption 5. *The wholesale and retail prices of refurbished products are always lower than the prices of new products ($w_r < w_n$ and $p_r < p_n$)* (Cahyani & Kurdhi, 2025).

Assumption 6. *It is assumed that $\alpha < Q$ with a representing the market potential of refurbished products and Q representing the market potential of new products when no refurbished products are available* (Pradana & Kurdhi, 2024).

Assumption 7. A government-authorized carbon emission limit of e_0 can be traded in the carbon market. Companies can sell and buy the carbon emission quota at the same price, which is $\mathrm{p_c}$.

Assumption 8. *All parameters are positive.*

Assumption 9. *In this study, the values of $\mathrm{p_n}$ and $\mathrm{p_r}$ are not constant. The demand function for new and refurbished products in this study is written as follows*

$$q_n = Q - b(p_n - p_r) \ldots (1)$$

$$q_r = \alpha - l\,p_r + b(p_n - p_r) \ldots (2)$$

where $b(p_n - p_r)$ is the number of high-end customers who switch from new to refurbished products, and b denotes the cannibalization coefficient. In the demand for refurbished products α is expressed as the potential market for refurbished products, $l\,p_r$ is the potential consumers who do not buy refurbished products with l being the price elasticity of refurbished products and pr being the price of refurbished products (Pradana & Kurdhi, 2024).

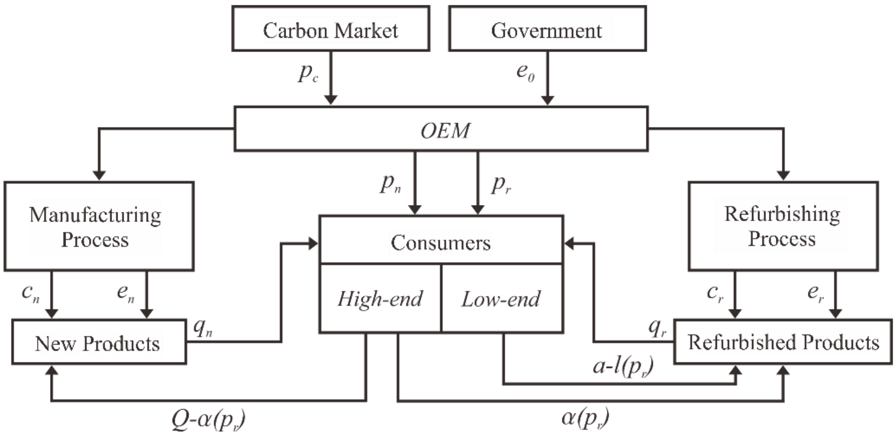


Figure 1. Production Process Scheme of Direct Distribution Refurbishing Model (C)

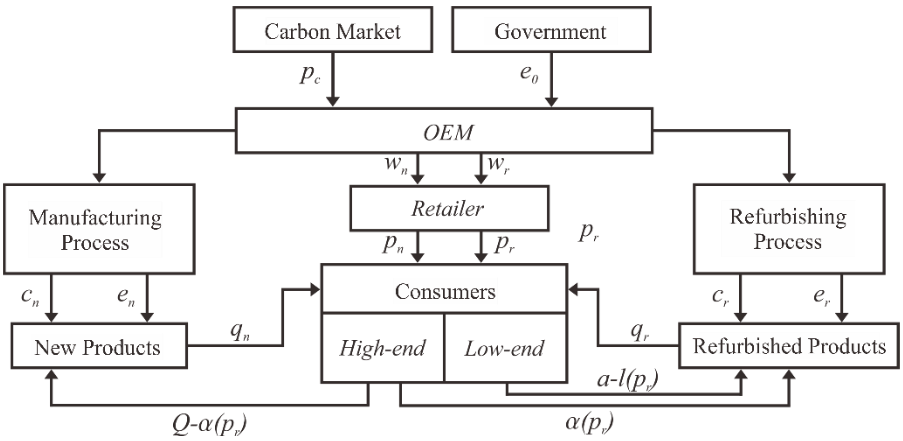


Figure 2. Production Process Schematic of Refurbishing Model Indirect Distribution (M)

Table 2 presents a comprehensive summary of the symbols and their respective definitions utilized within this model.

Table 2. Notations and associated description

Symbol	Description
w_n	Wholesale price of new products
w_r	Wholesale price of refurbished products
p_n	New product price
p_r	Refurbished product price
q_n	New product production quantity
q_r	Refurbished product production quantity
c_n	Production cost of new product per unit
c_r	Production cost of refurbished product per unit
e_0	Carbon emission limit allowed by the government
e_n	Carbon emissions generated in the manufacture of one unit of new product
e_r	Carbon emissions generated in the manufacture of one unit of refurbished product
e_u	Carbon emissions generated in the product use phase by consumers per unit
e_t	Carbon emissions generated in the exhaust phase of each unit
E	Total carbon emissions generated as environmental impact
Q	Potential market for new products when there are no refurbished products
a	Market potential for refurbished products
b	Cannibalization coefficient
l	The price elasticity of market demand for low-end customers
α	Number of high-end customers moving from new to refurbished products
P_O^C	OEM profits when refurbishing with direct distribution
P_O^M	OEM profits when refurbishing with indirect distribution
$*$	The superscript for the optimal value of decisions and profits functions

Direct Distribution Refurbishing Model (OEM), The profit function for OEM refurbishing consists of three main components: total profit from the sale of new and refurbished products and the trading or purchase of carbon emissions on the carbon market. To maximize its profit, the OEM analyzes the optimal price and quantity responses in the following manner:

$$\max_{p_n, p_r} P_O^C = (p_n - c_n)q_n + (p_r - c_r)q_r + p_c(e_0 - e_n q_n - e_r q_r). \qquad \dots (3)$$

OEM maximize the respective profit functions after substituting the demand functions in Equations (1) and (2) so that the direct distribution refurbishing model is obtained as follows :

$$\max_{p_n, p_r} P_O^C = (p_n - c_n)(Q - b(p_n - p_r))) + (p_r - c_r)(a - lp_r + b(p_n - p_r))) \qquad \dots (4)$$
$$+p_c(e_0 - e_r(Q - b(p_n - p_r)) - e_r(a - lp_r + b(p_n - p_r))).$$

Proposition 1. Based on Equation (4), the optimal values for $p_n^{C*}, p_r^{C*}, q_n^{C*}, q_r^{C*}, \mathrm{P}_O^{C*}$ are as follows :

$$p_n^{C*} = \frac{ab + (b + l)Q + bl(c_n + e_n p_c)}{2bl}, \qquad \dots (5)$$

$$p_r^{C*} = \frac{a + Q + lc_r + le_r p_c}{2l}, \qquad \dots (6)$$

$$q_n^{C*} = \frac{1}{2}(Q + b(-c_n + c_r + (-e_n + e_r)p_c)), \quad \dots (7)$$

$$q_r^{C*} = \frac{1}{2}(a + bc_n - (b + l)c_r + (be_n - (b + l)e_r)p_c), \quad \dots (8)$$

$$P_O^{C*} = \frac{1}{4bl}(a^2b + 2abQ + (b+l)Q^2 + bl(bc_n^2 + c_r(-2a + (b + l)c_r) \quad \dots (9)$$
$$+2(2e_0 - (Q + bc_r)e_n + (-a + (b+l)c_r)e_r)p_c + (be_n^2 - 2be_n$$
$$e_r + (b+l)e_r^2)p_c^2 - 2c_n(Q + bc_r + b(-e_n + e_r)p_c))).$$

Through the application of backward induction, the optimal solution for the OEM refurbishing model can be ascertained. This entails verifying that equation (4) represents a strictly concave function, which can be accomplished by analyzing the Hessian matrix. Subsequently, by substituting the given assumptions into the equation, we derive the specific values of $p_n^{O*}, p_r^{O*}, q_n^{O*}, q_r^{O*}, \mathrm{P}_O^{O*}$, which constitute the optimal solution. Indirect Distribution Refurbishing Model (OEM+Retailer), The profit function for OEM refurbishing consists of three main components: total profit from the sale of new and refurbished products and the trading or purchase of carbon emissions on the carbon market.To maximize its profit, the OEM analyzes the optimal price and quantity responses in the following manner:

$$\max_{w_n, w_r} P_O^M = (w_n - c_n)q_n + (w_r - c_r)q_r + p_c(e_0 - e_nq_n - e_rq_r) \quad \dots (10)$$

The retailer profit function is defined as the total revenue from the sale of new and refurbished products by the retailer. The total retailer revenue is obtained by summing the production profit of new products with the production profit of refurbished products..To maximize its profit, the retailer analyzes the optimal price and quantity responses in the following manner:

$$\max_{p_n, p_r} P_R^M = (p_n - w_n)q_n + (p_r - w_r)q_r \quad \dots (11)$$

Each parties maximize their respective profit functions after substituting the demand functions in Equations (1) and (2) so that the indirect distribution refurbishing model is obtained as follows:

$$\max_{w_n, w_r} P_O^M = (w_n - c_n)\big(Q - b(p_n - p_r)\big) + (w_r - c_r)\big(a - lp_r + b(p_n - p_r)\big) \quad \dots (12)$$
$$+$$
$$p_c(e_0 - e_n(Q - b(p_n - p_r)) - e_r(a - lp_r + b(p_n - p_r))),$$

$$\max_{p_n, p_r} P_R^M = (p_n - w_n)(Q - b(p_n - p_r)) + (p_r - w_r)(a - lp_r + b(p_n - p\_r)) \quad \dots (13)$$

Proposition 2. Based on Equation (12) and (13), the optimal values for $w_n^{M*}, w_r^{M*}, p_n^{M*}, p_r^{M*}, q_n^{M*}, q_r^{M*}, \mathrm{P}_O^{M*}, \mathrm{P}_R^{M*}$ are as follows :

$$w_n^{M*} = \frac{ab + (b+l)Q + bl(c_n + e_np_c)}{2bl}, \quad \dots (14)$$

$$w_r^{M*} = \frac{a + Q + lc_r + le_rp_c}{2l}, \quad \dots (15)$$

$$p_n^{M*} = \frac{3ab + 3(b+l)Q + bl(c_n + e_np_c)}{4bl}, \quad \dots (16)$$

$$p_r^{M*} = \frac{3(a + Q) + lc_r + le_rp_c}{4l}, \quad \dots (17)$$

$$q_n^{M*} = \frac{1}{4}(Q + b(-c_n + c_r + (-e_n + e_r)p_c)), \quad \dots (18)$$

$$q_r^{M*} = \frac{1}{4}(a + bc_n - (b + l)c_r + (be_n - (b + l)e_r)p_c), \quad \dots (19)$$

$$P_O^{M*} = \frac{1}{8bl}(a^2b + 2abQ + (b+l)Q^2 + bl(bc_n^2 + c_r(-2a + (b + l)c_r) + 2(4e_0 - (Q + bc_r)e_n + (-a + (b + l)c_r)e_r)p_c + (be_n^2 - 2be_ne_r + (b+l)e_r^2)p_c^2 - 2c_n(Q + bc_r + b(-e_n + e_r)p_c))), \quad \dots (20)$$

$$P_R^{M*} = \frac{1}{16bl}(b(a + bcn - (b + l)cr + (ben - (b + l)er)pc(a + Q - l(c_r + e_rp_c) + (ab + (b + l)Q - bl(cn + enpc))(Q + b(-cn + cr + (-en + er)pc)))). \quad \dots (21)$$

Through the application of backward induction, the optimal solution for the OEM and retailer refurbishing model can be ascertained. This entails verifying that equation (12) and (13) represents a strictly concave function, which can be accomplished by analyzing the Hessian matrix. Subsequently, by substituting the given assumptions into the equation, we derive the specific values of $w_n^{M*}, w_r^{M*}, p_n^{M*}, p_r^{M*}, q_n^{M*}, q_r^{M*}, \mathrm{P}_O^{M*}, \mathrm{P}_R^{M*}$, which constitute the optimal solution.

Model analysis was carried out by comparing each optimum value in the two models. Some of the optimum values compared are the new product price (p_n^*), refurbished product price (p_r^*), new product quantity (q_n^*), refurbished product quantity (q_r^*), and OEM profit (P_O^*) with combined OEM and retailer profit (P_G^*).

Optimal Price and Quantity Comparison between Models C and M.

Remark 1. *The price of a new product in the direct distribution refurbishing model is lower than the price of a new product in the indirect distribution refurbishing model or $p_n^{C*} < p_n^{M*}$ when the carbon emission condition used in making the new product is $e_n < e_{n1}$ with,*

$$e_{n1} = \frac{ab + (b+l)Q - blc_n}{blp_c}$$

The price of new products in the C refurbishing model is lower than the price of new products in the M refurbishing model. This is because in the C refurbishing model, distribution is carried out directly to consumers, so the price of new products is the price given directly from the OEM and there are no other parties involved to make a profit. The price given by OEMs is much cheaper than the price of new products whose distribution must go through other parties such as retailers.

Remark 2. *The price of refurbished products in the direct distribution refurbishment model is lower than the price of refurbished products in the indirect distribution refurbishment model or $p_r^{C*} < p_r^{M*}$ when the condition of carbon emissions used in the manufacture of refurbished products is $e_r < e_{r1}$ with,*

$$e_{r1} = \frac{a + Q - lc_r}{lp_c}.$$

The price of refurbished products in the C refurbishing model is lower than the price of refurbished products in the M refurbishing model. This is because in the C refurbishing model, distribution is carried out directly to consumers, so the price of refurbished products is the price given directly from the OEM and there are no other parties involved to make a profit. The price given by OEMs is much cheaper than the price of refurbished products whose distribution must go through other parties such as retailers.

Remark 3. *The quantity of new products in the direct distribution refurbishing model is higher than the quantity of new products in the indirect distribution refurbishing model or $q_n^{C*} < q_n^{M*}$ under the condition that the carbon emissions used in the manufacture of new products $e_n < e_r + \eta$ with,*

$$\eta = \frac{Q - bc_n + bc_r}{bp_c}.$$

The production quantity of new products in the direct distribution refurbishing model is higher than the production quantity of new products in the indirect distribution refurbishing model because the selling price of new products in the direct distribution refurbishing model is lower than the selling price of new products in the indirect distribution refurbishing model ($p_n^C < p_n^M$). This is in accordance with the law of supply and demand, namely if the price offered is lower, there will be more demand for new products. Due to the high demand, the quantity of new products produced in the direct distribution refurbishing model is higher than the quantity of new products produced in the indirect distribution refurbishing model.

Remark 4. *The quantity of refurbished products in the direct distribution refurbishment model is higher than the quantity of refurbished products in the indirect distribution refurbishment model or $q_r^{C*} < q_r^{M*}r$ when the carbon emission conditions used in producing the new product $e_n < e_{n3}$ and the carbon emission conditions used in producing the refurbished product $e_r < e_{r3}$ with,*

$$e_{n3} = -\frac{a + bc_n - (b+l)c_r + e_r p_c}{bp_c} \text{ and } e_{r3} = \frac{a + bc_n - (b+l)c_r + be_n p_c}{(b+l)p_c}.$$

The production quantity of refurbished products in the direct distribution refurbishment model is higher than the quantity of refurbished products in the indirect distribution refurbishment model because the selling price of refurbished products in the direct distribution refurbishment model is lower than the selling price of refurbished products in the indirect distribution refurbishment model ($p_r^C < p_r^M$)This is in accordance with the law of supply and demand, namely if the price offered is lower, there will be more demand for refurbished products.

Comparison of Profit between Models C and M

Remark 5. *OEM profits in the direct distribution refurbishing model are greater than the combined profits of OEMs and retailers in the indirect distribution refurbishing model $P_O^{C*} > P_G^{M*}$) when the price elasticity condition is $l_1 < l < l_2$ with,*

$$l_1 = -\frac{1}{2b(c_r + e_r p_c)^2} Q^2 + b^2(c_n - c_r)^2 - 2abc_r - 2b\big(ae_r + b(c_n - c_r)(-e_n + e_r)\big)p_c + b^2(e_n - e_r)^2 p_c^2 - 2bQ(c_n + e_n p_c) + \sqrt{\begin{matrix}((Q + b(-c_n + c_r + (-e_n + e_r)p_c)^2(Q^2 + b(bc_n^2 + c_r - 2(2a+Q) + bc_r - 2((Q \\ +bc_r)e_n + (2a + Q - bc_r)e_r)p_c + b(e_n - e_r)^2 p_c^2 - 2c_n(Q + bc_r + b(-e_n + e_r)p_c\end{matrix}},$$

$$l_2 = -\frac{1}{2b(c_r + e_r p_c)^2} \mathrm{Q}^2 + 2\mathrm{bQ}(\mathrm{c_n} + \mathrm{e_n p_c}) + \mathrm{b}(-\mathrm{b}(\mathrm{c_n} - \mathrm{c_r})^2 + 2\mathrm{ac_r} + 2\big(\mathrm{ae_r} + \mathrm{b}(\mathrm{c_n} - \mathrm{c_r})(-\mathrm{e_n} + \mathrm{e_r})\big)\mathrm{p_c} - \mathrm{b}(\mathrm{e_n} - \mathrm{e_r})^2\, \mathrm{p_c^2} + \sqrt{\begin{matrix}((Q + b(-c_n + c_r + (-e_n + e_r)p_c)^2(Q^2 + b(bc_n^2 + c_r - 2(2a+Q) + bc_r - 2((Q \\ +bc_r)e_n + (2a + Q - bc_r)e_r)p_c + b(e_n - e_r)^2 p_c^2 - 2c_n(Q + bc_r + b(-e_n + e_r)p_c\end{matrix}},$$

$$\text{s.t. } b > \frac{2b\big(((Q+bc_r)e_n + (2a+Q-bc_r)e_r)p_c + c_n(Q + bc_r + b(e_n+e_r)p_c)\big) - Q^2}{bc_n^2 + c_r(-2(2a+Q) + bc_r) + b(e_n - e_r)^2 p_c^2}.$$

OEM profits in the direct distribution refurbishing model are higher than the combined profits of OEMs and retailers in the indirect distribution refurbishing mode (Zhou, Sheu, & Choi). This is because the production quantity of new and refurbished products in the direct distribution refurbishing model is greater than the production quantity of new and refurbished products in the indirect distribution refurbishing model. The larger production quantity of new and refurbished products affects the production costs incurred (Li, R, & Liu, 2019).The greater the production quantity of new and refurbished products will lead to cheaper raw material prices so that production costs will also be lower (Poonia, Sangwan, Kulshretha, & Shah, 2025). In addition to the high production quantity of new and refurbished products in the direct distribution refurbishing model, this lower production cost also causes the profits earned by OEMs in the direct distribution refurbishing model to be higher than the profits earned by OEMs and retailers in the indirect distribution refurbishing model.

The findings suggest that direct distribution channel structure offers significant economic advantages for OEMs through economies of scale and reduced channel margins From a Channel structure perspective, the decentralized structure (indirect distribution) consistently shows different performance outcones compared to centralized operations (Zhang Y. , Zhang, Hu, & Yang, 2025)However, the optimal channel structure decision depends on various factors including production cost, market conditions, and enviromental regulations (Li & Shi, 2022).

The integration of cap and trade mechanism with distribution channel decisions adds complexity to these relationship The Carbon emission constraints influence not only the production decisions but also the overall profitability comparison between direct and indirect channel (Li & Shi, 2022) Companies must carefully evaluate the trade-offs between channel structure effeciency and enviromental compliance cost when designing their refurbishing supply chains (Poonia, Sangwan, Kulshretha, & Shah, 2025).

Comparison of Environmental Impacts between Models O and A

Remark 6. *The refurbishing model with indirect distribution is more environmentally friendly than the direct distribution refurbishing model ($E^{M*} < E^{C*}$) when $c_r < c_{r1}$ with,*

$$c_{r1} = \frac{1}{be_n - (b+l)e_r + be_t - le_u}((bc_n(-e_r + et) - a(e_r + e_u) - Q(e_t + e_u) + be_n^2 p_c$$
$$+e_r\big((b+l)e_r - be_t\ + le_u\big)p_c + e_n(-Q + bc_n + b(-2e_r + e_t)p_c)).$$

The indirect distribution refurbishing model is more environmentally friendly than the direct distribution refurbishing model (Zhou, Sheu, & Choi). This is because the total carbon emissions generated as an impact on the environment are influenced by the production quantity. The greater the production quantity, the more massive the production process will be, and the more waste will be released (Qin, Chen, Zhang, & Ding, 2023). The production quantity (Ganguly, Das & Maiti, 2025) of new and refurbished products in the direct distribution model is more than the production quantity in the indirect distribution model (Zhou, Sheu, & Choi). This causes the total carbon emissions generated as an impact on the environment in the direct distribution refurbishing model to be higher than the environmental impact in the indirect distribution refurbishing model (Ganguly, Das, & Maiti, 2025).

The relationship between production volume and environmental impact has been well documented in the literature.life cycle analysis studies have shown that refurbished products present significantly lower global warming potential compared to new products, primarily due to the avoidance of material extraction and production phases (Wiche, Pequeño, & Granato, 2022)However, the scale of operations and channel structure significantly influence the overall enviromental outcomes (Fatorachian & Kazemi, 2025). From a circular supply chain perspective, the transition from linear to circular models requires careful consideration of ligistics optimization and emission reduction techniques (Fatorachian & Kazemi, 2025). The indirect distribution model, while potentially less profitable, demonstrates better enviromental performance by limiting production volumes and reducing the overall carbon footprint of operations. Furthermore, the integration of cilcular economy principles with distribution channel decisions reveals important trade- offs between economic and enviromental objectives (Torshizi, Mousapour Mamoudan, & yazdani, 2026). Decision- makers must balance profit maximization with enviromental sustainability goals, particulary under stringent cap and trade regulations (Ganguly, Das, & Maiti, 2025).

The findings underscore the importance of considering enviromental impacts alongside economic performance when designing refurbishing supply chains (Kumar et al, 2023). While direst distribution offers higher profitability, indirect distribution provides superior enviromental outcomes, suggesting that policy interventions may be necessary to encourage more sustainable channel structures (Qin, Chen, Zhang, & Ding, 2023).

RESULTS AND DISCUSSION

The application of the refurbishing model in this study uses the example of an electronic product, namely a smartphone. Parameter values taken from several sources are used to apply the refurbishing model. Referring to the parameter values $e_0 = 1$, $e_n = 0.15$, $p_c = 0.25$, $c_n = 0.4$ are taken. In accordance with assumptions 4 and 5, the values $c_r < c_n$ and $e_r < e_n$ are taken with reference to Yang et al. (2020), namely $c_r = 0.3$ and $e_r = 0.1$. The market potential of new products when there are no refurbished products is assumed to be $Q = 600$. In accordance with assumption 7, the value of $a < Q$ is taken so that the parameter value of the market potential of refurbished products is set ($a = 500$). The cannibalization coefficient is set at $b = 2$, and the price elasticity of refurbished products is $l = 2.5$. Referring to Yang et al. (2020), the carbon emission generated in the product use phase by consumers is $e_u = 0.3$. Carbon emissions generated in the disposal phase refer to Esenduran et al. (2015), which is

$e_t = 0.006$. Furthermore, the parameter values are substituted into the model. The optimum value of each decision variable and the optimum profit for each model are presented in the following table 3.

Table 3. Optimum value Model C and M

Parameter	Model O	Model A
p_n^*	\$370.219	\$555.109
p_r^*	\$220.163	\$330.081
w_n^*	-	\$370.219
w_r^*	-	\$220.163
q_n^*	299888	249706
q_r^*	249706	124853
P_O^*	\$165796	\$82894
P_R^*	−	\$41446
P_G^*	\$165796	\$124430
E^*	236.631	118.316

The differences in variable values in the direct distribution and indirect distribution refurbishing models are compared against the carbon emissions used in the manufacture of en and er products. So that the comparison graph is obtained in Figure 3 – 10.

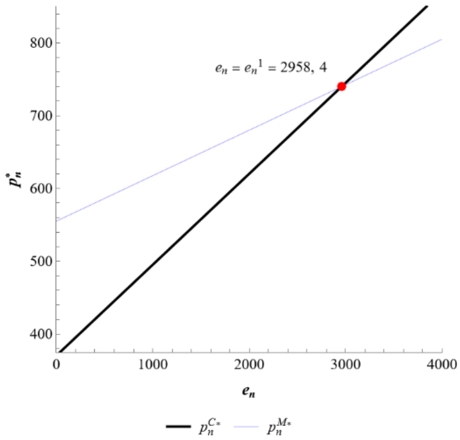


Figure 3. Effects of e_n on p_n^{C*} and p_n^{M*}

Based on Figure 3, the price of new products in the direct distribution refurbishing model is lower than the price of new products in the indirect distribution refurbishing model $p_n^{C*} < p_n^{M*}$ when the carbon emissions used in making new products $e_n < e_{n1}$. In both graphs, there is an intersection point when the value of $e_{n1} = 2958.4$. The graph shows that the greater the carbon emissions used in the manufacture of new products, the greater the selling price of new products to consumers. There is a change in the condition of the selling price of new products between the two models, when $e_{n1} = 2958.4$ the selling price of new products in the direct distribution refurbishing model is higher than the selling price of new products in the indirect distribution refurbishing model $p_n^{C*} > p_n^{M*}$.

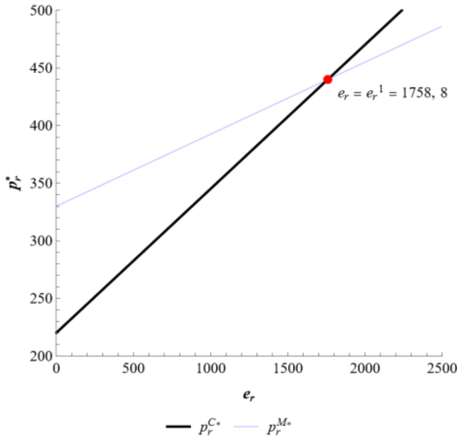
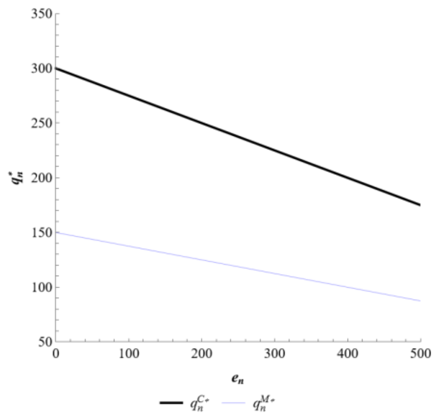
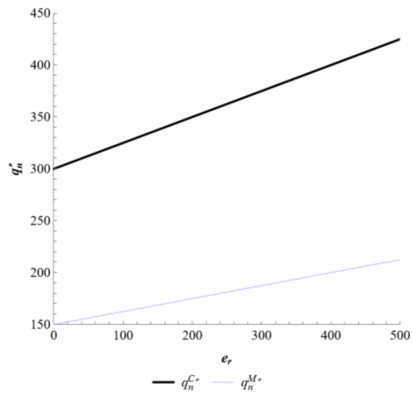


Figure 4. Effects of e_n on p_r^{C*} and p_r^{M*}

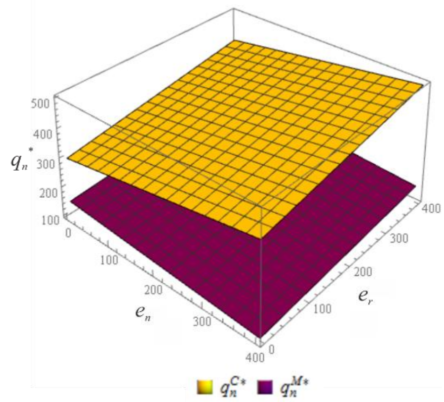
Based on Figure 4, the price of refurbished products in the direct distribution refurbishment model is lower than the price of refurbished products in the indirect distribution refurbishment model $p_r^{C*} < p_r^{M*}$ when the carbon emissions used in the manufacture of refurbished products $e_r < e_{r1}$. In both graphs, there is an intersection point when the value of $e_{r1} = 1758.8$. The graph shows that the greater the carbon emissions used in making refurbished products, the greater the selling price of refurbished products to consumers. There is a change in the condition of the selling price of refurbished products between the two models, namely when $e_{r1} = 1758.8$ the selling price of refurbished products in the direct distribution refurbishing model is higher than the selling price of refurbished products in the indirect distribution refurbishing model $p_r^{C*} > p_r^{M*}$.



(a)



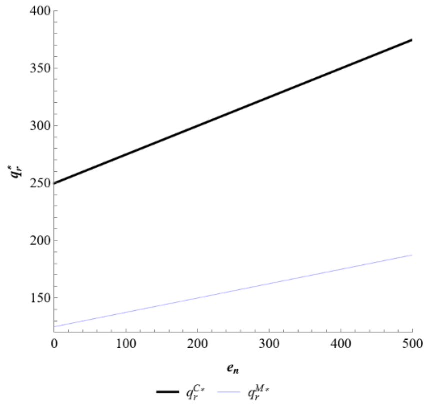
(b)



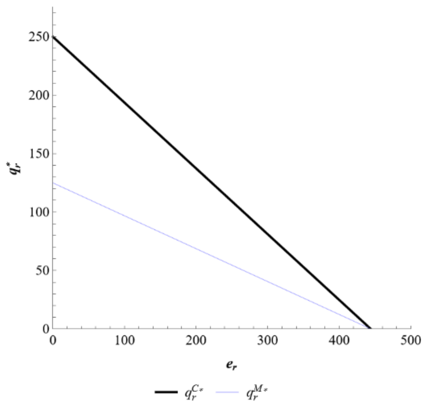
(c)

Figure 5. Effects of (a) e_n and (b) e_r on q_n^*

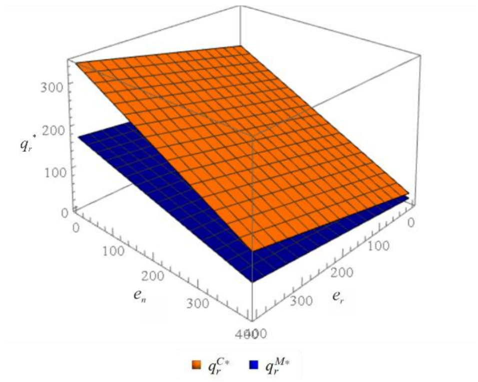
Based on Figures 5 (a) and (b), the production quantity of new products in the direct distribution refurbishing model is higher than the production quantity of new products in the indirect distribution refurbishing model $q_n^{C*} > q_n^{M*}$ under the condition that $e_n < e_{n2}$ or $e_r > e_{r2}$ with the value of $e_{n2} = 1199.7$ and $e_{r2} = -1199.7$. In Figure 5 (a), it can be seen that the greater the carbon emissions used in the manufacture of refurbished products, the smaller the production quantity of new products. Meanwhile, Figure 5 (b) shows that the greater the carbon emissions used in manufacturing refurbished products, the greater the quantity of new product production.



(a)



(b)



(c)

Figure 6. Effects of (a) e_n and (b) e_r on q_r^*

Based on Figures 6 (a) and (b), the production quantity of refurbished products in the direct distribution refurbishing model is higher than the production quantity of refurbished products in the indirect distribution refurbishing model $q_r^{C*} > q_r^{M*}$ under the condition of $e_n < e_{n3}$ or $e_r > e_{r3}$ with the value of $e_{n3} = -444.022$ and $e_r 3 = 444.022$ In Figure 6 (a), it can be seen that the greater the carbon emissions used in making new products, the greater the production quantity of refurbished products. Meanwhile, Figure 6 (b) shows that the greater the carbon emissions used in manufacturing refurbished products, the smaller the production quantity of refurbished products.

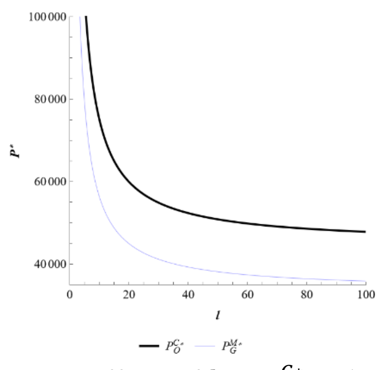


Figure 7. Effects of l on P_O^{C*} and P_G^{M*}

Based on Figure 7, OEM profits in the direct distribution refurbishing model are greater than OEM and retailer profits in the indirect distribution refurbishing model $P_O^{C*} > P_O^{M*} > P_R^{M*}$ when the carbon emissions used in the production of refurbished products $e_r < e_{r4}$ and $e_r < e_{r5}$.

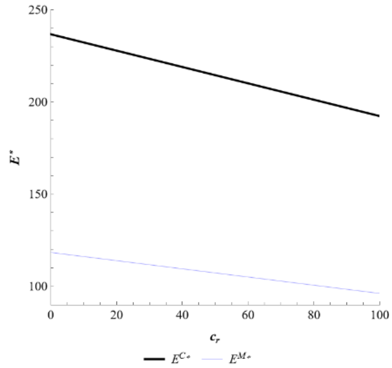


Figure 8. Effects of c_r on E^{C*} and E^{M*}

Based on Figure 8, it is evident that the indirect distribution refurbishing model is more environmentally friendly than the direct distribution refurbishing model $E^{M*} < E^{C*}$ under the condition that the production cost of refurbished products $c_r < c_{r1}$. Figure 8 also shows that the higher the production cost of refurbished products, the smaller the carbon emissions.

Sensitivity Analysis

Sensitivity analysis was conducted to analyze the impact of changes in parameter values on the optimal value of each model. Sensitivity analysis was conducted based on several changes in parameter values, namely new product market potential (Q), cannibalization coefficient (b), price elasticity (l), carbon price (p_c), and carbon emissions used in making new products (e_n).

Sensitivity Analysis for Different $\boldsymbol{Q}$ Values

The potential market value of the new product (Q) was changed from 600 to 1000. The graph of sensitivity analysis to Q can be seen in Figures 9 and 10.

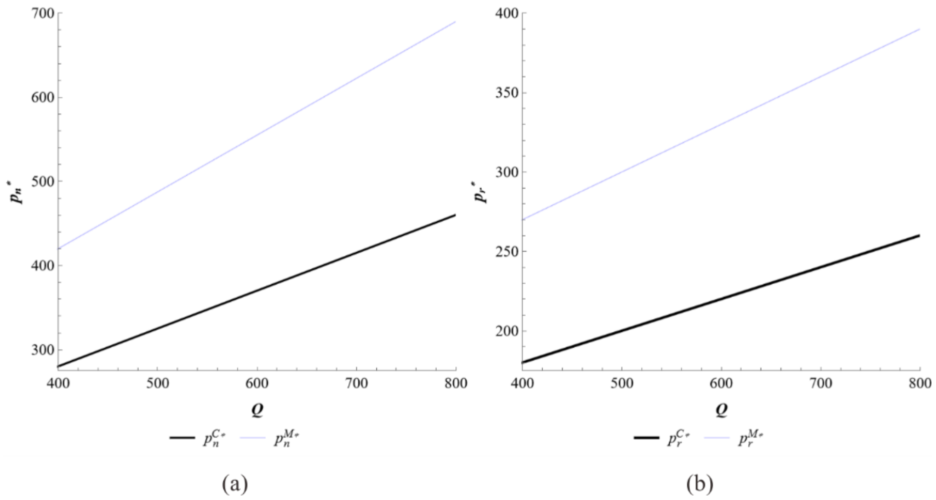
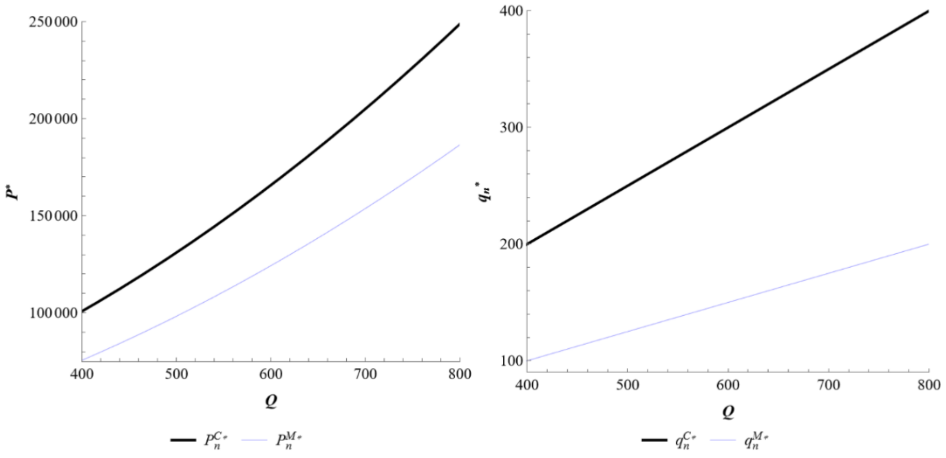


Figure 9. The impact of Q on (a) the selling price of new products, and (b) the selling price of refurbished products

Figure 9 (a) shows that when the potential market of the new product increases, the selling price of the new product also increases. The selling price of new products in model C (p_n^{C*}) increased by 48.61%, from $\$370{,}219$ to $\$550{,}219$. Meanwhile, the selling price of new products in model M (p_n^{M*}) increased by 48.63%, from $\$555{,}109$ to $\$825{,}109$. Figure 9 (b) shows that when the potential market for new products increases, the selling price of refurbished products also increases. The selling price of refurbished products in model C (p_r^{C*}) increased by 36.34%, from $\$220{,}163$ to $\$300{,}163$. Meanwhile, the selling price of refurbished products in model M (p_r^{M*}) increased by 36.35%, from \$330,081 to \$450,081.



(a) (b)

Figure 10. The impact of Q on (a) new product production quantity, and (b) OEM profit in model C and combined profit in model M

Figure 10 (a) shows that when the potential market for new products increases, the production quantity of new products also increases. The production quantity of new products in model C (q_n^{C*}) increased by 66.69%, from \$299,888 to \$499,888. The production quantity of new products in model M (q_n^{M*}) also increased by 66.69%, from \$149,944 to \$249,944. Figure 10 (b) shows that when the potential market for new products increases, OEM profits in model C and combined OEM and retailer profits in model M increase. OEM profits in model C (P_O^{C*}) increased by 110.93%, from \$165796 to \$349713. The combined profit of OEMs and retailers in model M (P_M^{G*}) increased by 110.93%, from \$124341 to \$262275.

*Sensitivity Analysis for Different **b** Values*

The value of the cannibalization coefficient (b) was changed from 2 to 4. The graphs of the sensitivity analysis on b can be seen in Figures 11, 12 and 13.

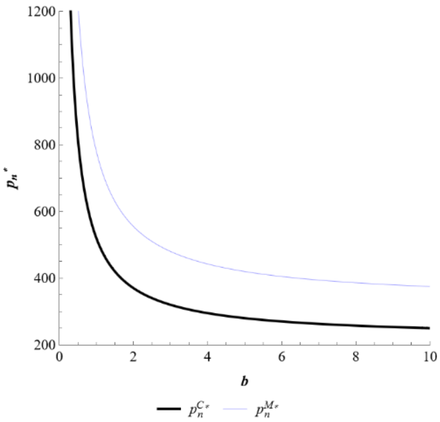
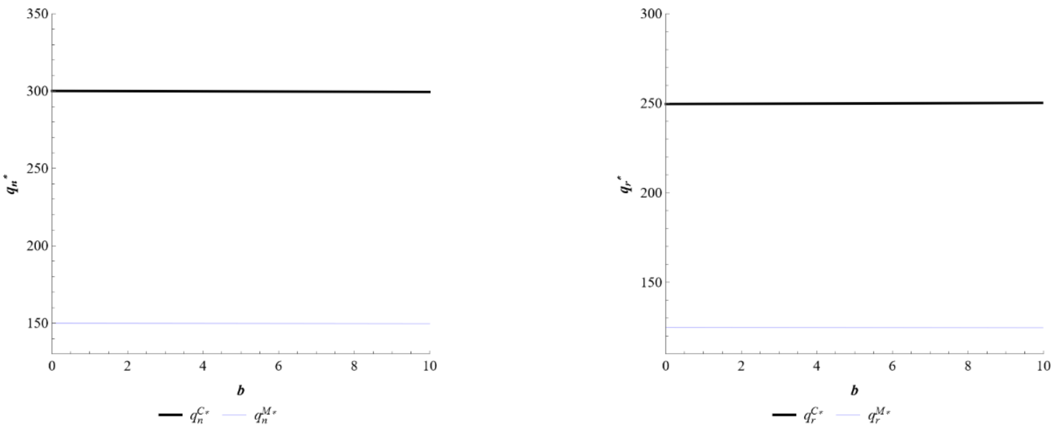


Figure 11. The impact of b on the selling price of new products

Figure 11 shows that as the cannibalization coefficient increases, the selling price of the new product decreases. The selling price of a new product in model C (p_n^{C*}) decreases by 20.2%, from \$370,219 to \$295,219. Meanwhile, the selling price of the new product in model M (p_n^{M*}) decreases by 20.3%, from \$555,109 to \$442,609.



(a) (b)

Figure 12. The impact of b on (a) new product production quantity, and (b) refurbished product production quantity

Figure 12 (a) shows that when the cannibalization coefficient increases, the production quantity of new products decreases. The production quantity of new products in model C (q_n^{C*}) decreases by 0.04%, from \$299,888 to \$299,775. The production quantity of new products in model M (q_n^{M*}) also decreased by 0.04%, from \$149,944 to \$149,888. Figure 12 (b) shows that when the cannibalization coefficient increases, the production quantity of refurbished products also increases. The production quantity of refurbished products in model C (q_r^{C*}) increased by 0.04%, from \$249,706 to \$249,819. The production quantity of refurbished products in model M (q_n^{M*}) also increased by 0.04%, from 124,853 to \$124,909.

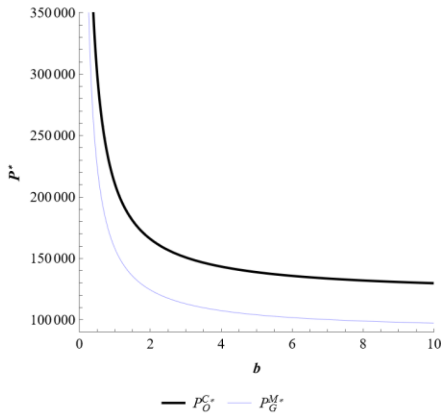
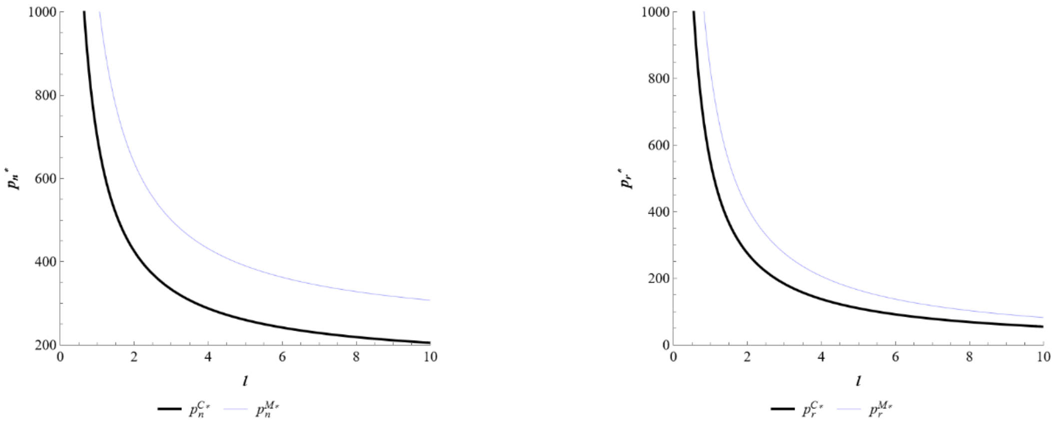


Figure 13. The impact of b on OEM profit in model C and OEM + Retailer profit in model M

Figure 13 shows that when the cannibalization coefficient (b) increases, the OEM's profit in model C and the combined profit of OEM and retailer in model M decrease. OEM profits in model C (P_O^{C*}) decreased by 13.57%, from \$165796 to \$143296. The combined profit of OEMs and retailers in model M (P_G^{M*}) decreased by 13.57%, from \$124341 to \$107466.

Sensitivity Analysis for Different l Values

The value of price elasticity (l) was changed from 2.5 to 6. The graphs of the sensitivity analysis on l can be seen in Figures 14, 15, and 16.



(a) (b)

Figure 14. The impact of l on (a) the selling price of new products, and (b) the selling price of refurbished products

Figure 14 (a) shows that when the price elasticity increases, the selling price of the new product decreases. The selling price of new products in model C (p_n^{C*}) decreased by 34.66%, from \$370,219 to \$241,885. Meanwhile, the selling price of new products in model M (p_n^{M*}) decreased by 34.68%, from \$555,109 to \$362,609. Figure 14 (b) shows that when price elasticity increases, the selling price of refurbished products decreases. The selling price of refurbished products in model C (p_r^{C*}) decreased by 58.3%, from \$220,163 to \$91,83. Meanwhile, the selling price of refurbished products in model M (p_r^{M*}) decreased by 58.32%, from \$330,081 to \$137,581.

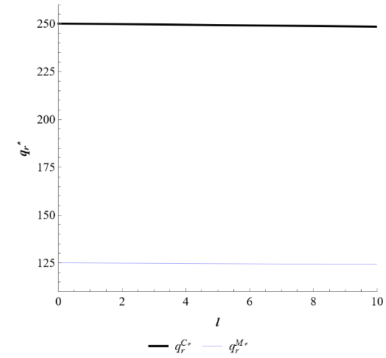


Figure 15. The impact of l on refurbished product production quantity

Figure 15 shows that as the price elasticity increases, the production quantity of refurbished products decreases. The production quantity of refurbished products in model C (q_r^{C*}) decreased by 0.23%, from \$249,706 to \$249,138. The production quantity of refurbished products in model M (q_n^{M*}) also decreased by 0.23%, from \$124,853 to \$124,569.

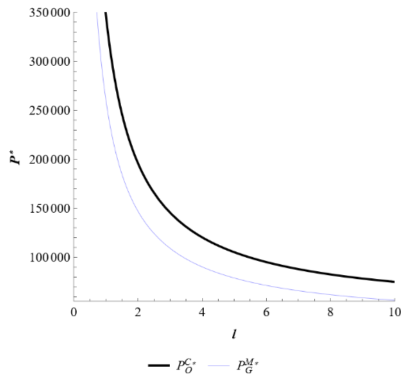
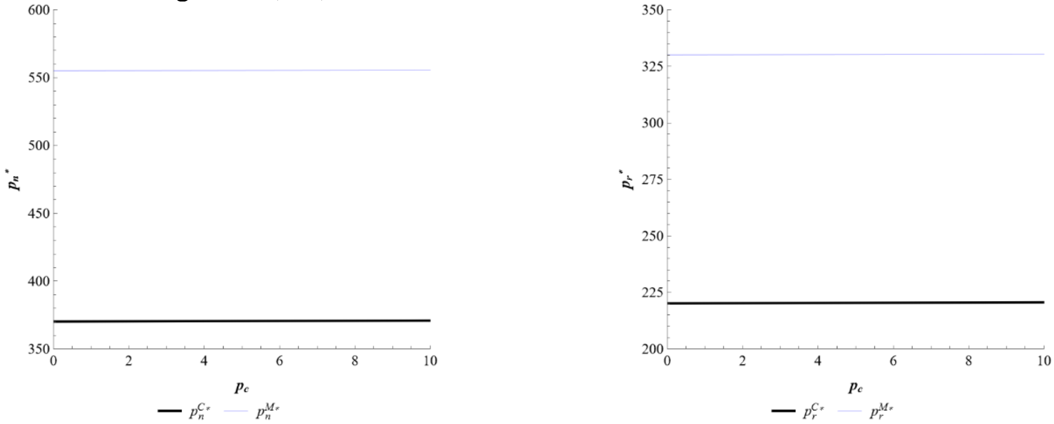


Figure 16. The impact of l on OEM profit in model C and OEM + Retailer profit in model M

Figure 16 shows that when the price elasticity (l) increases, OEM profits in model C and the combined OEM and retailer profits in model M decrease. OEM profits in model C (P_O^{C*}) decreased by 42.6%, from \$165796 to \$95213. The combined OEM and retailer profit in model M (P_G^{M*}) decreased by 42.6%, from \$124341 to \$71403.

Sensitivity Analysis for Different $\boldsymbol{p_c}$ Values

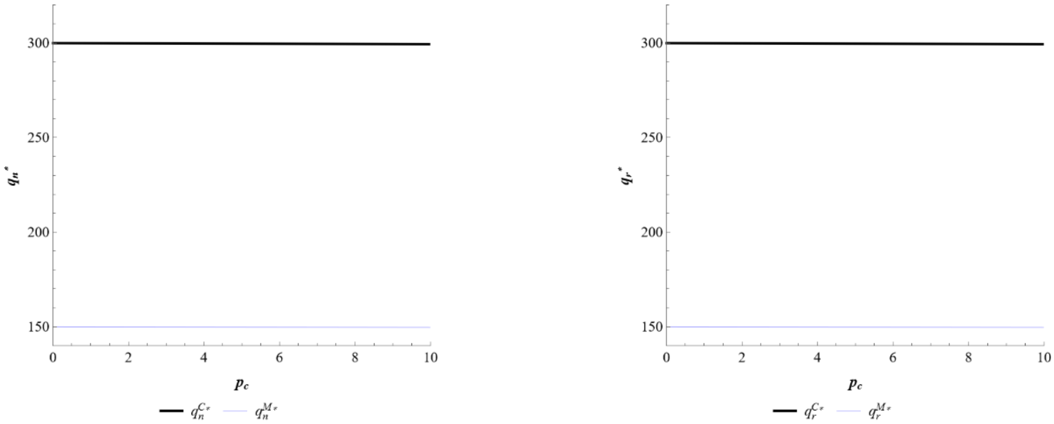
The value of carbon price (p_c) was changed from 0.25 to 1. The graphs of the sensitivity analysis to p_c can be seen in Figures 17, 18, and 19.



(a) (b)

Figure 17. The impact of p_c on (a) the selling price of new products, and (b) the selling price of refurbished products

Figure 17 (a) shows that when the carbon price increases, the selling price of the new product increases. The selling price of new products in model C (p_n^{C*}) increases by 0.02%, from \$370,219 to \$370,275. Meanwhile, the selling price of new products in model M (p_n^{M*}) has increased by 0.005%, from \$555,109 to \$555,138. Figure 17 (b) shows that when the carbon price increases, the selling price of refurbished products increases. The selling price of refurbished products in model C (p_r^{C*}) increased by 0.02%, from \$220,163 to \$220,2. Meanwhile, the selling price of refurbished products in model M (p_r^{M*}) increased by 0.006%, from \$330,081 to \$330.1.



(a) (b)

Figure 18. The impact of p_c on (a) new product production quantity, and (b) refurbished product production quantity

Figure 18 (a) shows that when the carbon price increases, the quantity of new product production decreases. The quantity of new product production in model C (q_n^{C*}) decreased by 0.01%, from \$299,888 to \$299.85. The production quantity of new products in model M (q_n^{M*}) also decreased by 0.01%, from \$149,944 to \$149,925. Figure 18 (b) shows that when the carbon price increases, the production quantity of refurbished products decreases. The production quantity of refurbished products in model C

(q_r^{C*}) decreased by 0.02%, from \$249,706 to \$249.65. The production quantity of refurbished products in model M (q_n^{M*}) also increased by 0.02%, from \$124,853 to \$124,825.

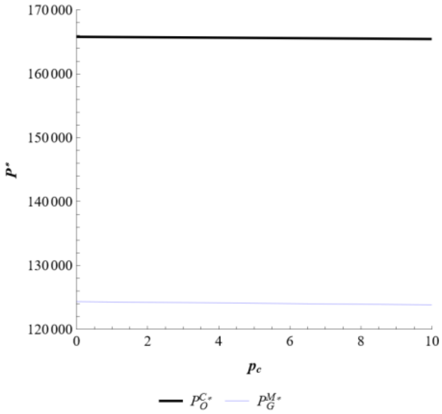
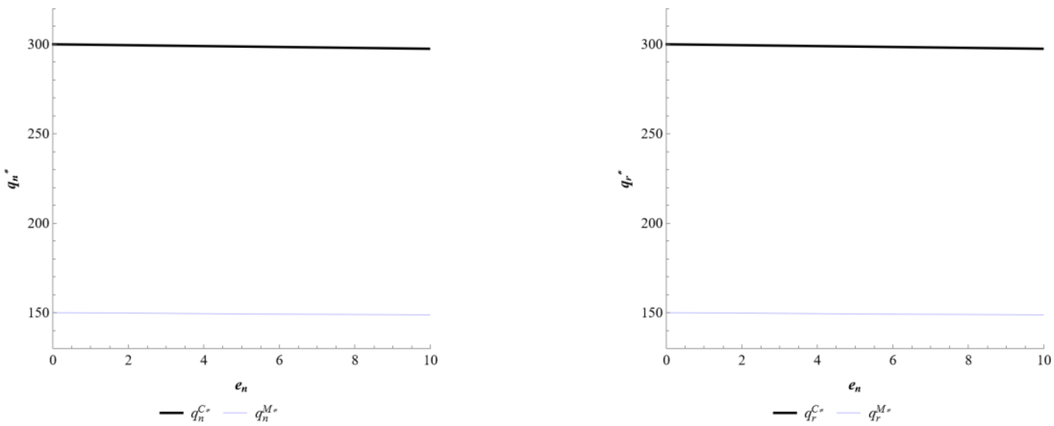


Figure 19. The impact of p_c on OEM profit in model C and OEM + Retailer profit in model M

Figure 19 shows that when carbon prices increase, OEM profits in model C and combined OEM and retailer profits in model M decrease. OEM profits in model C (P_O^{C*}) decreased by 0.02%, from \$165796 to \$165771. The combined OEM and retailer profit in model M (P_G^{M*}) decreased by 0.03%, from \$124341 to \$124302.

Sensitivity Analysis for Different e_n Values

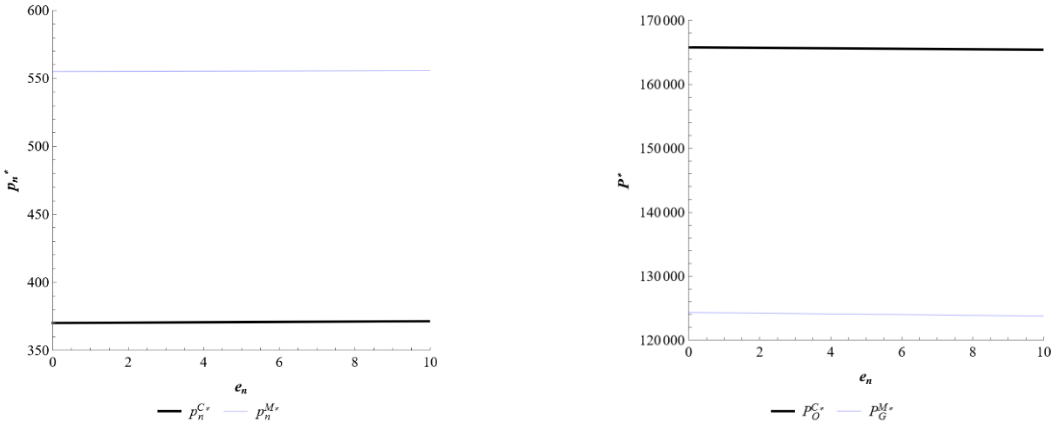
The value of carbon emissions used in the manufacture of new products (e_n) was changed from 0.15 to 0.8. Graphs of the sensitivity analysis to e_n can be seen in Figures 20 and 21.



(a) (b)

Figure 20. The impact of e_n on (a) new product production quantity, and (b) refurbished product production quantity

Figure 20 (a) shows that when the carbon emissions used for new product manufacturing increases, the quantity of new product production decreases. The production quantity of new products in model C (q_n^{C*}) decreased by 0.05%, from \$299,888 to \$299,725. The production quantity of new products in model M (q_n^{M*}) also decreased by 0.05%, from \$149,944 to \$149,863. Figure 20 (b) shows that when the carbon emissions used in manufacturing new products increase, the production quantity of refurbished products also increases. The production quantity of refurbished products in model C (q_r^{C*}) increased by 0.06%, from \$249,706 to \$249,869. The production quantity of refurbished products in model M (q_n^{M*}) also increased by 0.06%, from \$124,853 to \$124,934.



(a) (b)

Figure 21. The impact of e_n on (a) the selling price of new products, and (b) OEM profit in model C and OEM + Retailer profit in model M

Figure 21 (a) shows that as the carbon emissions used in manufacturing the new product increases, the selling price of the new product increases (Yavari, Mihankah, & Jozani, 2024). The selling price of new products in model C (p_n^{C*}) increases by 0.02%, from $\$370{,}219$ to $\$370.3$. Meanwhile, the selling price of new products in model M (p_n^{M*}) increased by 0.007%, from $\$555{,}109$ to $\$555.15$. Figure 21 (b) shows that when the carbon emissions used in the manufacture of new products (e_n) increases, the OEM profit in model C and the combined OEM and retailer profit in model M decrease (Yavari et al, 2024). OEM profits in model C (P_O^{C*}) decreased by 0.01%, from $\$165796$ to $\$165772$. The combined OEM and retailer profit in model M (P_G^{M*}) decreased by 0.03%, from $\$124341$ to $\$124304$.

From the results of the sensitivity analysis that has been carried out, it is obtained that each parameter has an influence on the benefits of each party. The parameter that when increased in value has the most significant effect on increasing OEM profits in model C (P_O^{C*}) and combined OEM and retailer profits in model M (P_G^{M*}) is the market potential for new products (Q). While the parameter that when increased in value has the most significant effect on decreasing OEM profits in Model C (P_O^{C*}) and combined OEM and retailer profits in model M (P_G^{M*}) is the price elasticity of refurbished products (l). To obtain greater profits, it is also necessary to consider other parameters such as the cannibalization coefficient (b) which is quite influential in reducing OEM profits in model C (P_O^{C*}) and the combined profits of OEMs and retailers in model M (P_G^{M*}). The decrease in profit against the cannibalization coefficient means that if more consumers switch to refurbished products, the more OEM and retailer revenue decreases. So we conclude that to maximize profit, we need to increase the parameter Q, and decrease the parameters b and l. For other parameters such as the price of carbon pc and carbon emissions resulting from the manufacture of new products e_n is not very influential because of its insignificant shift.

The better profitability of direct distribution or Model C under a system of cap and trade regulations also controverts existing conventional wisdom regarding the relative efficiency of distribution channels. This observation implies the existence of additional incentives for a vertically integrated structure owing to environmental regulations, contrary to the conventional notion of the efficiency of a vertically integrated structure driven by forces of transactional costs. The elimination of intermediary margins, common in direct distributions, allows OEMs to benefit from full profit margins with competitive pricing.

CONCLUSION

In model C, the OEM's optimum profit reaches $\$165796$ with an optimum selling price for new products of $\$370{,}219$ and an optimum selling price for refurbished products of $\$220{,}163$. Whereas in model M the combined OEM optimum profit reached $\$124431$, with an optimum wholesale price of new products of $\$370{,}219$, an optimum wholesale price of refurbished products of $\$220{,}163$, a selling price of new products of $\$555{,}109$, and a selling price of refurbished products of $\$330{,}081$. The results of the sensitivity analysis show that the refurbishing model involving one actor (model C) is more profitable when changes are made to the values of all parameters. Parameter Q significantly affects the increase in OEM profits in model C (P_O^{C*}) and the combined OEM and retailer profits in model M (P_G^{M*}). While the parameter (l) has the most significant effect on decreasing OEM profits in Model C (P_O^{C*}) and the combined profits of OEMs and retailers in model M (P_G^{M*}). To maximize profits, it is necessary to increase parameter Q, and decrease parameters b and l. For other parameters such as the price of carbon pc and carbon emissions resulting from the manufacture of new products en is not too influential because the shift is not too significant.

Furthermore, policymakers need to realize the possibility of cap-and-trade regulations affecting structural supply chain issues. The preference for direct distribution under a carbon-constrained system implies that environmental regulations can affect vertical integration, and thus influence competition structures. The cap-and-trade of carbon policy should account for structural implications. The contributions of this study are multifaceted: First integrated analysis of distribution channel choice, refurbishing operations, and cap-and-trade policy; Development of comparative optimization models that can rigorously evaluate channel performance under environmental constraints; Extensive sensitivity analysis of the key value drivers across different distribution configurations; Providing evidence that environmental regulations create structural incentives toward vertical integration in supply chains of the circular economy. Some limitations of the models, despite their significance, need to be acknowledged. For one, the models assume deterministic demand, implying the addition of demand uncertainty for a higher level of realism. Second, the models solve for single-period optimization. Incorporating a multi-period model with economic models of inventory management and carbon banking can increase the insight generated. Third, the competitive interactions of various OEMs and retailers, though assumed implicitly, need to be explicitly modeled. An oligopolistic market structure could change things. Fourth, firm-level factors, though represented by parameter estimates from literature review, could play a role.

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AUTHOR CONTRIBUTIONS

The authors contributed to this research as follows: Conceptualization, YPP and NAK; Methodology, YPP; Software, YPP; Validation, YPP, NAK, and MBS; Formal Analysis, YPP and SIZG; Investigation, YPP; Resources, BTO; Data Curation, YPP; Writing – Original Draft Preparation, YPP; Writing – Review & Editing, YPP, NAK, and MBS; Visualization, YPP and SIZG; Supervision, NAK and BTO; Project Administration, YPP; Funding Acquisition, BTO. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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