ISSN 2616-5902 Vol. 7, Issue 3: 24-31, DOI: 10.25236/AJBM.2025.070304

Analysis of E-Commerce Platform Sales Models from a Traffic Competition Perspective

Yaping Niu[1,a,*], Peng Lu[1]

[1] *School of Economics and Management, Shaanxi University of Science and Technology, Xi'an, China*
[a] *niuyaping0218@163.coml*
**Corresponding author*

Abstract: *In an increasingly competitive e-commerce landscape, traffic has become a crucial factor influencing sales models. This paper examines various e-commerce sales models through the lens of traffic dynamics. By developing two traffic game models—one under the resale model and the other under the agency model—we analyze the optimal decisions of e-commerce platforms and merchants. Additionally, we explore how different parameters impact equilibrium decisions. Our analysis of equilibrium profits under both sales models reveals that e-commerce platforms achieve higher profits under the agency model. Finally, we validate our findings through numerical examples. The insights gained from this study aim to serve as a reference for e-commerce platforms and merchants seeking to optimize their sales strategies.*

Keywords: *Resale model, Agency model, Traffic game*

1. Introduction

The platform economy is currently experiencing rapid growth. According to data from Statista, global social e-commerce sales surged to an impressive $992 billion in 2022 and are projected to reach approximately $8.5 trillion by 2030. As a key factor in the digital economy, data is becoming increasingly valuable. Unlocking the full potential of digital assets has become a crucial aspect of digital economic development. Among these assets, traffic data plays a vital role in shaping the platform economy. In e-commerce, acquiring and investing in traffic data is especially critical.

Traffic data refers to the information generated by user interactions on a platform, including visits, browsing, clicks, purchases, shares, and reviews. This data can be analyzed to understand user behavior, optimize product offerings, enhance user experience, and drive commercial success for platforms. Platform companies benefit from strong cross-network effects, attracting large numbers of users and forming extensive traffic resource pools[1]. Merchants selling goods or services rely on these platforms to acquire user traffic, which they must convert into sales to grow their businesses[2]. Consequently, a competitive dynamic emerges between platform companies and merchants over traffic data.

Currently, e-commerce platforms primarily operate under two sales models: reselling and agency selling[3]. While existing research has explored how merchants and platforms choose between these models under different conditions—such as uncertain demand [4], multi-channel competition [5], quality-price trade-offs[6], live e-commerce[7], green investment[8], and platform type[9]—there has been little focus on sales model selection in the context of traffic data competition. To address this gap, this paper examines how traffic data influences the optimal decisions of platforms and merchants under these two sales models by developing relevant analytical models.

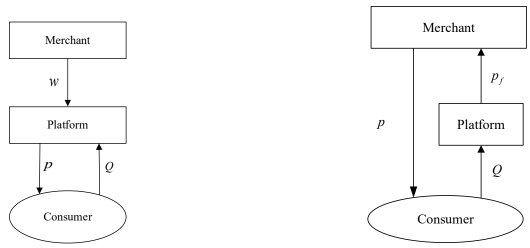
2. Model Description and Assumptions

2.1. Supply Chain Structure

This paper mainly establishes two scenarios: the resale model and the agency model. Considering the supply chain structure consisting of an e-commerce platform, merchants and consumers, in the resale model, merchants wholesale products to the e-commerce platform, and the platform then resells the products to consumers. The platform is equivalent to a retailer in the traditional retail system. In the agency model, merchants can sell products directly to consumers through the platform, and the platform

ISSN 2616-5902 Vol. 7, Issue 3: 24-31, DOI: 10.25236/AJBM.2025.070304

extracts a certain percentage of the sales as an intermediary service fee for providing this model. The supply chain structure diagrams are shown in Figure 1.



(a) Resale Model (b) Agency Model

Figure 1 Supply chain structure diagram under two sales models

2.2. Assumptions

This paper mainly establishes two scenarios: the resale model and the agency model. Considering the supply chain structure consisting of an e-commerce platform, merchants and consumers, in the resale model, merchants wholesale products to the e-commerce platform, and the platform then resells the products to consumers. The platform is equivalent to a retailer in the traditional retail system. In the agency model, merchants can sell products directly to consumers through the platform, and the platform extracts a certain percentage of the sales as an intermediary service fee for providing this model. The supply chain structure diagrams are shown in Figure 1.

Assumption 1 Merchants and e-commerce platforms are rational decision makers who pursue maximizing their own interests.

Assumption 2 Referring to the study of A, assume that the inverse linear demand functions of the commodities are as follows;

$$p_i = a - bQ \tag{1}$$

where, $Q = Q_0 + \beta f$, Q_0 represents the demand for goods that is not affected by traffic data, and βf represents the promoting effect of traffic data on the demand for goods.

Assumption 3 The effort cost of an e-commerce platform to attract users to visit the platform is a quadratic function $\frac{1}{2}kf^2$.

2.3. Parameter Description

The parameters used in the model and their meanings are shown in Table 1

Table 1: Parameter Description.

Parameter	Description
a	The market size
b	Inverse price elasticity
Q	Total demand for goods
Q_0	the demand for goods that is not affected by traffic data
β	Traffic demand coefficient
k	Traffic cost coefficient
f^j	Traffic data under different sales models
p_f	The price of traffic data
γ	Commission ratio under agency model
w	Wholesale prices under the resale model
c	Unit cost of goods
π_e^j	Profits of e-commerce platforms under different sales models
π_m^j	Merchants' profits under different sales models
$j = (R, A)$	R stands for resale model, A stands for agency model

ISSN 2616-5902 Vol. 7, Issue 3: 24-31, DOI: 10.25236/AJBM.2025.070304

3. Model

3.1. Resale Model R

In the resale model, the e-commerce platform purchases or wholesales goods from merchants, and then sells the goods to consumers through the platform's own traffic pool. The platform and merchants follow the Stackelberg game, and both the platform and the merchants follow their own interests. Assuming that in this model, the game order is: the merchant first determines its wholesale price, and the e-commerce platform determines its traffic investment based on consumer demand. At this time, the decision function faced by the e-commerce platform and the merchant is as follows:

The merchant’s decision function is:

$$\max \pi_m^R\left(w\right)=(w-c)Q \tag{2}$$

The decision function of the platform is:

$$\max \pi_e^R\left(f\right)=(p-w)Q-\frac{1}{2}kf^2 \tag{3}$$

Using the reverse method to solve, first derive the profit function of the platform, let $\frac{d\pi_e}{\partial f}=0$, the following results are obtained:

$$\frac{\partial \pi_e^R}{\partial f}=-fk-b\beta\left(q+f\beta\right)+\beta\left(a-bq-w-bf\beta\right)=0 \tag{4}$$

Solving the above equations yields the following result:

$$f=\frac{a\beta-2bQ_0\beta-w\beta}{k+2b\beta^2} \tag{5}$$

Substituting equation 5 into the merchant's profit function 2 and derive it. According to the profit maximization principle, let $\frac{d\pi_m}{dw}=0$ and we can get the optimal wholesale price w^{R^*}:

$$w^{R^*}=\frac{kQ_0+a\beta^2+c\beta^2}{2\beta^2} \tag{6}$$

Substituting the optimal wholesale price into equation 4, we get the optimal traffic input

$$f^{R^*}=\frac{\left(a-c-4bQ_0\right)\beta^2-kQ_0}{2\beta\left(k+2b\beta^2\right)} \tag{7}$$

According to Assumptions 2, substituting w^{R^*} and f^{R^*} into equation 1, we can get the optimal retail price p^{R^*} and the optimal order quantity Q^{R^*}

$$p^{R^*}=\frac{k\left(2a-bQ_0\right)+b\left(3a+c\right)\beta^2}{2\left(k+2b\beta^2\right)} \tag{8}$$

$$Q^{R^*}=\frac{kQ_0+\left(a-c\right)\beta^2}{2\left(k+2b\beta^2\right)} \tag{9}$$

Therefore, the optimal profit of merchants and e-commerce platforms is:

$$\pi_e^{R^*}=\frac{-3k^2{Q_0}^2-2kQ_0\left(-a+c+4bQ_0\right)\beta^2+\left(a-c\right)^2\beta^4}{8\beta^2\left(k+2b\beta^2\right)}$$

ISSN 2616-5902 Vol. 7, Issue 3: 24-31, DOI: 10.25236/AJBM.2025.070304

$$\pi_m^{R^*} = \frac{\left(kq + (a-c)\beta^2\right)^2}{4\beta^2\left(k + 2b\beta^2\right)}$$

Therefore, $\left(w^{R^*}, f^{R^*}, p^{R^*}, Q^{R^*}\right)$ constitutes the Nash equilibrium of the game between merchants and e-commerce platforms under the resale model.

Lemma1: The optimal wholesale price is inversely proportional to the flow demand coefficient and directly proportional to the flow cost coefficient. The optimal flow input is directly proportional to the flow demand coefficient and inversely proportional to the flow cost coefficient.

Proof: $\frac{dw^{R^*}}{d\beta} = -\frac{kQ_0}{\beta^3} < 0$; $\frac{dw^{R^*}}{dk} = \frac{Q_0}{2\beta^2} > 0$; $\frac{df^{R^*}}{dk} = -\frac{\left(a-c-2bQ_0\right)\beta}{2\left(k+2b\beta^2\right)^2} < 0$;

$$\frac{df^{R^*}}{d\beta} = \frac{k^2Q_0 + k\left(a-c+2bQ_0\right)\beta^2 + 2b\left(-a+c+4bQ_0\right)\beta^4}{2\beta^2\left(k+2b\beta^2\right)^2} > 0$$

Lemma 2: The optimal profit of a merchant is proportional to the traffic demand coefficient and inversely proportional to the traffic cost coefficient. The optimal profit function of an e-commerce platform is proportional to the traffic demand coefficient and inversely proportional to the traffic cost coefficient.

Proof:

$$\frac{d\pi_m^{R^*}}{d\beta} = \frac{k\left(kQ_0 + (a-c)\beta^2\right)\left(-kQ_0 + \left(a-c-4bQ_0\right)\beta^2\right)}{2\beta^3\left(k+2b\beta^2\right)^2} > 0$$

$$\frac{d\pi_m^{R^*}}{dk} = -\frac{\left(kQ_0 + (a-c)\beta^2\right)\left(-kQ_0 + \left(a-c-4bQ_0\right)\beta^2\right)}{4\beta^2\left(k+2b\beta^2\right)^2} < 0$$

$$\frac{d\pi_e^{R^*}}{d\beta} = \frac{k\left(3k^2{Q_0}^2 + 12bk{Q_0}^2\beta^2 + \left((a-c)^2 + 4b(-a+c)Q_0 + 16b^2{Q_0}^2\right)\beta^4\right)}{4\beta^3\left(k+2b\beta^2\right)^2} > 0$$

$$\frac{d\pi_e^{R^*}}{dk} = -\frac{3k^2{Q_0}^2 + 12bk{Q_0}^2\beta^2 + \left((a-c)^2 + 4b(-a+c)Q_0 + 16b^2{Q_0}^2\right)\beta^4}{8\beta^2\left(k+2b\beta^2\right)^2} < 0$$

3.2. Agency Model A

In the wholesale model, the e-commerce platform does not sell goods. Instead, it provides traffic to merchants and extracts a certain percentage as commission. For example, Taobao and Amazon charge a certain commission to platform merchants, and the commission percentage is an exogenous variable. Assuming that in this model, the platform and e-commerce merchants follow a three-stage perfect information dynamic game, and the game sequence is: the e-commerce platform first determines the sales price of its traffic, and the merchant determines the purchase volume of its traffic f. Merchants and e-commerce platforms follow the principle of profit maximization, and their decision functions are as follows:

The decision function of the e-commerce platform is:

$$\max \pi_e^A\left(p_f\right) = \gamma(p-c)Q + p_f f - \frac{1}{2}kf^2 \tag{10}$$

The merchant's decision function is:

$$\max \pi_m^A\left(Q, f\right) = (1-\gamma)(p-c)Q - p_f f \tag{11}$$

Use the reverse induction method to solve it. First, derive the merchant's profit function. Let $\frac{d\pi_m^A}{df} = 0$,

ISSN 2616-5902 Vol. 7, Issue 3: 24-31, DOI: 10.25236/AJBM.2025.070304

the following result is obtained:

$$\frac{d\pi_m^A}{df} = -p_f - b\beta\left(Q_0 + f\beta\right)\left(1-\gamma\right) + \beta\left(a-c-b\left(q+f\beta\right)\right)\left(1-\gamma\right) = 0 \tag{12}$$

Solving the equation yields the following result:

$$f^A = \frac{p_f + \left(a-c-2bQ_0\right)\beta\left(-1+\gamma\right)}{2b\beta^2\left(-1+\gamma\right)} \tag{13}$$

Substitute f^A into the profit function of the e-commerce platform, let $\frac{d\pi_e}{dp_f} = 0$, solve to get the optimal traffic pricing $p_f^{A^*}$

$$p_f^{A^*} = \frac{\left(a-c-2bQ_0\right)\beta\left(k-2b\beta^2\left(-1+\gamma\right)\right)\left(-1+\gamma\right)}{-k+2b\beta^2\left(-2+\gamma\right)} \tag{14}$$

Substituting f into formula 13, we get the optimal total amount of traffic purchased:

$$f^{A^*} = \frac{\left(a-c-2bQ_0\right)\beta}{k-2b\beta^2\left(-2+\gamma\right)} \tag{15}$$

The optimal sales volume and retail price are as follows:

$$Q^{A^*} = Q_0 + \frac{\left(a-c-2bQ_0\right)\beta^2}{k-2b\beta^2\left(-2+\gamma\right)} \tag{16}$$

$$p^{A^*} = a - bQ_0 + \frac{b\left(a-c-2bQ_0\right)\beta^2}{-k+2b\beta^2\left(-2+\gamma\right)} \tag{17}$$

The equilibrium profit of merchants and e-commerce platforms is:

$$\pi_m^{A^*} = (1-\gamma)(p^{A^*}-c)Q^{A*} - p_f^{A^*} f^{A^*} \tag{18}$$

$$\pi_e^{A^*} = \gamma(p^{A^*}-c)Q^{A^*} + p_f^{A^*} f^{A^*} - \frac{1}{2}kf^{A^{*2}} \tag{19}$$

Therefore, $\left(f^{A^*}, p_f^{A^*}, p^{A^*}, Q^{A^*}\right)$ constitutes the Nash equilibrium under the agency model.

Lemma 3 The optimal traffic investment is inversely proportional to the traffic demand coefficient and directly proportional to the traffic cost coefficient. The optimal traffic pricing is directly proportional to the traffic demand coefficient and the traffic cost coefficient.

Proof:

$$\frac{df^{A^*}}{d\beta} = \frac{\left(a-c-2bQ_0\right)\left(k+2b\beta^2\left(-2+\gamma\right)\right)}{\left(k-2b\beta^2\left(-2+\gamma\right)\right)^2} > 0; \frac{df^{A^*}}{dk} = -\frac{\left(a-c-2bq\right)\beta}{\left(-k+2b\beta^2\left(-2+\gamma\right)\right)^2} < 0$$

$$\frac{dp_f^{A^*}}{d\beta} = -\frac{\left(a-c-2bq\right)\left(k^2+2bk\beta^2\left(1-2\gamma\right)+4b^2\beta^4\left(-2+\gamma\right)\left(-1+\gamma\right)\right)\left(-1+\gamma\right)}{\left(k-2b\beta^2\left(-2+\gamma\right)\right)^2} > 0$$

$$\frac{dp_f^{A^*}}{d\beta} = \frac{2b\left(a-c-2bq\right)\beta^3\left(1-\gamma\right)}{\left(k-2b\beta^2\left(-2+\gamma\right)\right)^2} > 0$$

Lemma 4 The optimal profit function of the e-commerce platform is proportional to the traffic demand coefficient and inversely proportional to the traffic cost coefficient; the optimal profit function of the merchant is inversely proportional to the traffic demand coefficient and directly proportional to the traffic cost coefficient.

ISSN 2616-5902 Vol. 7, Issue 3: 24-31, DOI: 10.25236/AJBM.2025.070304

Proof:

$$\frac{d\pi_e^{A^*}}{d\beta}=\frac{k\left(-a+c+2bQ_0\right)^2\beta}{\left(k-2b\beta^2\left(-2+\gamma\right)\right)^2}>0\,;\,\frac{d\pi_e^{A^*}}{dk}=-\frac{\left(-a+c+2bQ_0\right)^2\beta^2}{2\left(k-2b\beta^2\left(-2+\gamma\right)\right)^2}<0\,;$$

$$\frac{d\pi_m^{A^*}}{d\beta}=-\frac{4bk\left(a-c-2bQ_0\right)^2\beta^3\left(1-\gamma\right)}{\left(k-2b\beta^2\left(-2+\gamma\right)\right)^3}<0\,;\,\frac{d\pi_m^{A^*}}{dk}=\frac{2b\left(-a+c+2bq\right)^2\beta^4\left(-1+\gamma\right)}{\left(k-2b\beta^2\left(-2+\gamma\right)\right)^3}>0$$

4. Numerical analysis

In order to verify the above model, the influence of different parameters on the equilibrium solution is studied, the parameters are assigned, and numerical examples are analyzed. From an economic point of view, each equilibrium solution should be greater than 0, so the parameter should satisfy $\left(a-c-4bq\right)\beta^2-kQ_0>0$. Referring to the research of relevant scholars, under the condition of satisfying the parameter conditions, let $a=300$, $b=0.6$, $\beta=0.4$, $k=3$, $\gamma=0.3$. Parameter Q_0 represents the quantity that can be sold without the help of traffic resources, reflecting the sales volume generated by the merchant's own brand, service and other factors. Here we focus on the impact of traffic data on sales models. To simplify the analysis, let $Q_0=0$.

4.1. The Impact of β and k on π_i^j

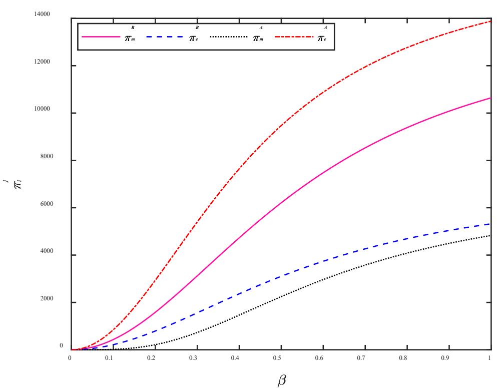


Figure 2 The impact of β on π_i^j

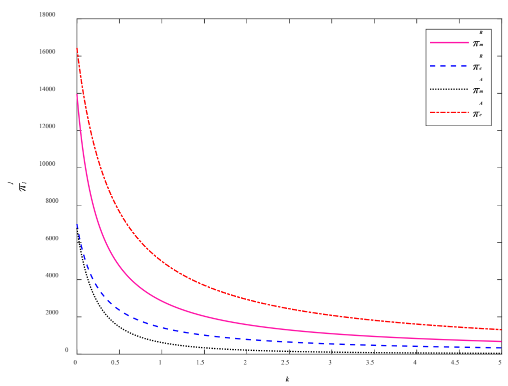


Figure 3 The impact of β on π_i^j

Figure 2 proves that as β increases, the equilibrium profit under different sales models also increases, and the equilibrium profit is proportional to the traffic demand coefficient. Secondly, under different sales models, the profits of e-commerce platforms and merchants also show different relationships. Under the resale model, the equilibrium profit of merchants is greater than that of e-commerce platforms, that is, $\pi_m^{R^*}>\pi_e^{R^*}$; under the agency model, the equilibrium profit relationship between e-commerce platforms and merchants is $\pi_m^{A^*}>\pi_e^{A^*}$. When the e-commerce platform chooses the agency model, the profit is the highest, showing $\pi_m^{A^*}>\pi_e^{R^*}$. For merchants, $\pi_m^{A^*}<\pi_m^{R^*}$, choosing the resale model is more advantageous.

As shown in Figure 3, as the traffic cost coefficient increases, the equilibrium profit under the two sales models decreases, that is, the optimal profit is inversely proportional to the traffic cost coefficient. The profit relationship under the two sales models shows $\pi_e^{A^*}>\pi_m^{R^*}>\pi_e^{R^*}>\pi_m^{A^*}$, and the profit of the e-commerce platform choosing the agency model is higher.

ISSN 2616-5902 Vol. 7, Issue 3: 24-31, DOI: 10.25236/AJBM.2025.070304

4.2. The Impact of β and k on p_f

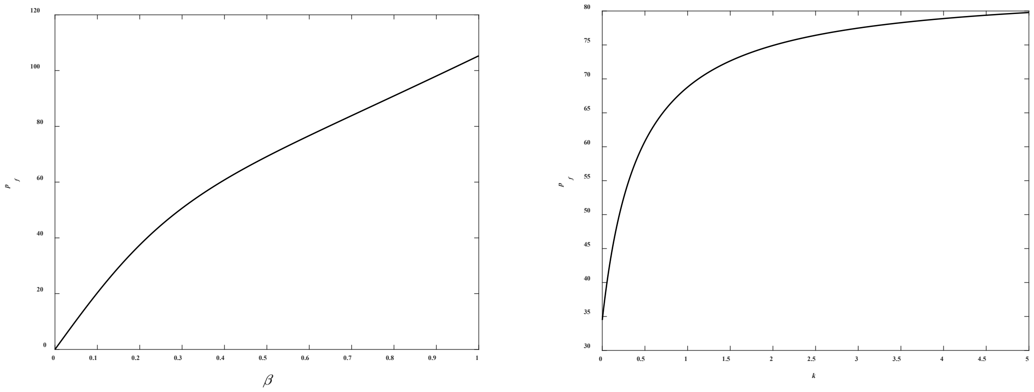


Figure 4 The impact of β and k on p_f

Figure 4 shows that when the demand coefficient and traffic cost coefficient of traffic data increase, the equilibrium price of traffic data also increases. For example, during shopping festivals or various online promotional activities, merchants' demand for accurate traffic surges, which leads to an increase in the price of traffic data. When the traffic cost of e-commerce platforms increases to maintain their own platforms, they will also appropriately increase the price of traffic data to ensure profitability.

4.3. The Impact of β and k on f^j

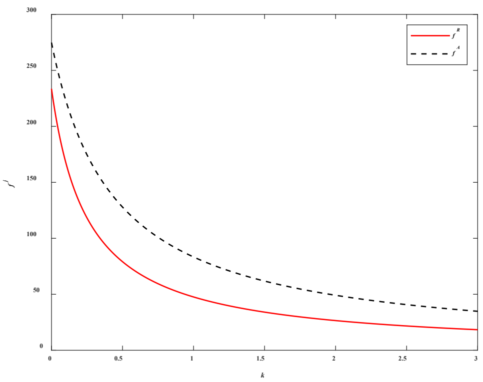


Figure 5 The impact of k on f^j

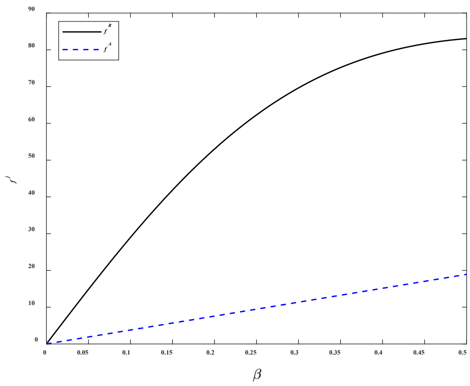


Figure 6 The impact of β on f^j

Figure 5 shows the impact of the traffic cost coefficient k on the optimal traffic input f^j under the two sales models, where the red solid line and the black dotted line correspond to f^R and f^A respectively. As can be seen from the figure, with the increase of k, both functions show a decreasing trend, but f^A is always higher than f^R in the entire interval, indicating that it is less sensitive to the change of k. In particular, when k takes a small value, f^j decreases faster, and when k gradually increases, the curve tends to be stable, indicating that the marginal impact of k on f^j gradually weakens.

Figure 6 shows the relationship between the traffic demand coefficient β and the traffic investment f^j. As β increases, both f^R and f^A show a growing trend. Specifically, in the resale mode, the traffic investment is larger and the sensitivity to β is stronger.

ISSN 2616-5902 Vol. 7, Issue 3: 24-31, DOI: 10.25236/AJBM.2025.070304

5. Conclusions

From the perspective of traffic dynamics, this paper constructs two models based on the resale and agency sales models of e-commerce platforms. Using game theory, we derive the optimal decisions for e-commerce platforms and merchants under these two models. We then analyze and validate our findings through numerical simulations. The study leads to the following key conclusions:

Considering traffic competition, e-commerce platforms achieve higher profits and greater advantages under the agency model. Conversely, merchants benefit more from the resale model. In the resale model, the platform's traffic investment after purchasing goods exceeds the total traffic merchants would acquire on their own. This occurs because, under resale, platforms are less sensitive to traffic cost coefficients but more sensitive to traffic demand coefficients compared to the agency model.

The optimal profits of both e-commerce platforms and merchants are directly proportional to the traffic demand coefficient and inversely proportional to the traffic cost coefficient. When the traffic demand coefficient rises, a fixed traffic investment generates greater demand, leading to a higher conversion rate and increased consumer purchases, ultimately boosting profits. Conversely, when the traffic cost coefficient rises, maintaining the same level of traffic becomes more expensive, reducing overall profits.

Optimal traffic investment is directly proportional to the traffic demand coefficient and inversely proportional to the traffic cost coefficient. Meanwhile, optimal traffic pricing is positively correlated with both coefficients. As both the traffic demand and cost coefficients increase, traffic pricing also rises. Additionally, when the traffic demand coefficient increases, product conversion rates improve, prompting e-commerce platforms to expand traffic supply and merchants to increase their traffic purchases.

Acknowledgements

This research was funded by the Social Science Foundation of Shaanxi Province (Program No. 2021R001); Scientific Research Program Funded by Shaanxi Provincial Education Department (Program No. 23JZ027), Natural Science Basic Research Program of shaanxi Province (2024JC-YBQN-0745). Thanks for the Wuhan East Lake High-Tech Development Zone (also known as the Optics Valley of China, or OVC) National Comprehensive Experimental Base for Governance of Intelligent Society.

References

[1] Rochet J-C, Tirole J. Platform competition in two-sided markets[J]. Journal of the European Economic Association, 2003, 1(4): 90–1029.

[2] He P, Shang Q, Pedrycz, W, et al. Short video creation and traffic investment decisions in social e-commerce platforms [J]. Omega, 2024, 128: 103129. https://doi.org/10.1016/j.omega.2024.103129.

[3] Yang, M. Green investment and e-commerce sales mode selection strategies with cap-and-trade regulation [J]. Computers & Industrial Engineering, 2023, 177: 109036.

[4] Yang M, Zhang T, Wang C X. The optimal e-commerce sales mode selection and information-sharing strategy under demand uncertainty[J]. Computers & Industrial Engineering, 2021, 162: 107718.

[5] Lin G, Dong X, Li Y, e al. Sales mode selection strategic analysis for manufacturers on e-commerce platforms under multi-channel competition[J]. Systems, 2022: 10(6):234.

[6] Lin Q, Chen L, Lin A. Study of the selection of sales mode of fresh e-commerce under quality-price competition [J]. Operations Research and Management Science, 2023: 32(2), 22.

[7] Yang L, Zheng C, Hao C. Optimal platform sales mode in live streaming commerce supply chains[J]. Electronic Commerce Research, 2024, 24(2): 1017–1070.

[8] Yang M. Green investment and e-commerce sales mode selection strategies with cap-and-trade regulation [J]. Computers & Industrial Engineering, 2023, 177: 109036.

[9] Dai H, Gao Q, Yan N, et al. What influences online sales across different types of e-commerce platforms? [J]. International Journal of Electronic Commerce, 2022, 26(3): 311–330.