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Subsidy policies for the grain supply chain considering postharvest loss of grain and agricultural pollutant emission in China

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Abstract: To reduce agricultural pollutant emission (APE) and postharvest loss of grain (PHLG), the Chinese government enacted a series of subsidy policies; however, the profit-oriented supply chain members are seriously lacking or reducing APE and PHLG efforts. To address this issue, we considered as the research objective a grain supply chain consisting of a producer, a retailer and the government. We proposed the concept and functional expressions of supply chain members' reduction efforts for APE and PHLG. We then proposed two main variables: the environmental innovation subsidy coefficient and the quantity attenuation factor of grain. According to the actual situation, four investment subsidy models were proposed. The results showed the following: *i*) supply chain members' equilibrium prices and incomes were negatively correlated with the degree of the producer's APE effort regardless of whether the supply chain members were investing in PHLG technology; *ii*) when the government subsidises APE and PHLG technology for other supply chain members, the government should stop subsidising the retailer's inputs in reduction loss technology to ensure that the government's own interests are not damaged; *iii*) the government's income was restricted by the degree of its subsidising of other supply chain members. This study provides a theoretical support for the government to formulate appropriate policies to reduce APE and PHLG, which is important for maintaining national food security.

Keywords: agricultural non-point source pollution; environmental innovation subsidy; grain loss; policy recommendations; quantity attenuation factor

Grain production is an important part of agricultural production activities. The issue of grain security is related to a country's stable development, and the degradation of environmental quality caused by grain production will affect the sustainable development of future generations. In SSA (sub-Saharan Afica), agricultural productivity has been increased through greater investment in agricultural mechanisation (Olase-

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hinde-Williams et al. 2020), but investigators in other studies have shown that agricultural production activities, meeting the basic demand for grains, have caused environmental pollution problems (Harizanova-Bartos and Stoyanova 2019; Tamagno et al. 2022). According to the Boston Consulting Group and XAG joint release (BCG and XAG 2022), 'The Road to Carbon Neutrality in Agriculture', agricultural activities account for 17% of global greenhouse gas emissions, and this proportion increases to 21% to 37% when grain storage and transportation are considered (Vermeulen et al. 2012). In addition, results from the 2nd National Water Resource Survey in China showed that approximately 60% of land resources were contaminated (Zhang et al. 2015). Although agricultural production activities entailed the release of several pollutants, the problem of postharvest loss of grain (PHLG) was extremely serious and indirectly threatened national food security. For instance, according to a Food and Agriculture Organization (FAO 2013) study, approximately one-third of the world's grain is wasted every year, with an economic loss of approximately USD 940 billion and greenhouse gas emissions from grain waste totaling 8% of global emissions (Van Gogh et al. 2017). According to the National Food and Strategic Reserves Administration (2021), PHLG in China exceeded 350 million tonnes, causing environmental damage and economic losses.

In China, the government had formulated relevant policies for subsidising PHLG reduction and agricultural pollutant emission (APE) management [see Appendix D in the Electronic Supplementary Material (ESM)]. Because of the profit-driven nature of grain supply chain members, the national average adoption of scientific grain storage equipment was less than 40%, and the transportation proportion of bulk grain was only 25% (National People's Congress of the PRC 2020). These data show that the existing PHLG reduction policy cannot mobilise the loss reduction efforts of the supply chain members; therefore, we should improve the PHLG reduction policy to mobilise the loss reduction efforts of the supply chain members. In addition, how will subsidising APE reduction affect PHLG reduction policy?

The key to solving these problems is to understand the subsidy and investment rules of supply chain members considering their APE and PHLG reduction efforts. Related research is focused on in the next section.

Firstly, we address APE and its subsidy strategy. Since 1980, relevant agricultural pollution prevention and control measures were taken in China and achieved initial results, but there were still deficiencies in agricultural pollution prevention and control. In recent years, agricultural pollution has attracted domestic and foreign scholars to study it as an important branch of global environmental pollution (Agboola and Bekun 2019; Gokmenoglu et al. 2020; Balogh 2023). According to Dhakal et al. (2022), the global agricultural sector contributes approximately 22% of greenhouse gas emissions. Agriculture accounts for use of 70% of global water resources. Chemicals from fertilisers and pesticides used in agricultural activities are discharged from farmland into bodies of water, leading to the pollution of water resources. For example, agricultural activities in China have led to significant water eutrophication and pollution, with more than 90% of lakes and rivers affected by varying degrees of eutrophication. Thus, from a Chinese perspective, agriculture serves as a major source of environmental pollution and waste generation. Nagendran (2011) outlined the complexity of agricultural waste, its effects and possible management options and also established an international database on agricultural waste. Agricultural pollution was a typical nonpoint source pollution, and most studies on agricultural pollution were in three areas: pesticide and fertiliser pollution (Tan et al. 2022), soil pollution (Wei et al. 2023) and water pollution (Zou et al. 2023). Research on agricultural pollution has focused mainly on three aspects: countermeasure research, monitoring and controlling (Duan et al. 2022; Hou et al. 2022). Agricultural pollution subsidy strategies were a hot topic of discussion among scholars (Chen et al. 2017; Chandio et al. 2022), but they mostly focused on green agricultural subsidies (Peng et al. 2022; Yi et al. 2023). To encourage supply chain members to reduce agricultural pollution effectively, Chen et al. (2017) studied the effects of environmental innovation subsidies (EISs) and output subsidies on agricultural pollution reduction, and they concluded that the EISs outperformed the output subsidies in reducing agricultural pollution and increasing output quantity. On the basis of these results, Zhang et al. (2021) conducted a study with results showing that a mixed subsidy strategy based on EISs and output subsidies was effective in reducing agricultural pollution and increasing output.

Secondly, we address PHLG and its subsidy strategy. Research on PHLG in the grain supply chain has focused mainly on factors influencing it and countermeasures. Generally speaking, the influencing factors that contribute to grain loss at each postharvest stage were similar, so scholars mainly analysed it according to harvest (Hou et al. 2021), storage (Arthur et al. 2023) and transportation (Mogale et al. 2016). In addi-

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tion, some of them focused on the whole supply chain (Bendinelli et al. 2019). Nyambo (2015) found that the degree of superiority and inferiority of grain seeds affected postharvest losses. Yusuf and He (2011) found hermetic grain storage could help farmers produce more revenue by reducing postharvest loss. In addition, there are many studies on PHLG reduction strategies, but the investigators in these studies ignored the grain producers' degree of effort towards postharvest loss reduction and the game relationships among supply chain members, such as in the study of loss reduction in harvesting by Guo et al. (2019). There are also scholars focused on the optimisation of loss reduction models (Fu et al. 2019). On the basis of the quantum game concept, Li et al. (2022) studied the effects of the supply chain members' degree of effort towards reduction loss on their incomes from the two aspects of the reduction loss effort and postharvest loss. At present, most research is performed through statistical analysis and experimental methods. By conducting a randomised controlled trial with panel data from 1 200 smallholders in Uganda and evaluating an improved storage technology, Omotilewa et al. (2018) found that the technology could reduce average storage losses by 61% to 70%. An and Ouyang (2016) integrated market equilibrium among farmers, stochastic crop yields and postharvest loss into the design of the grain supply chain system to propose a bilevel robust optimisation model with applications to case studies in the American state of Illinois and in Brazil.

Finally, we address subsidy strategies of the grain supply chain considering APE and PHLG. Investigators in most studies used lifecycle assessment (Cakar et al. 2020), stochastic optimisation (Cattaneo et al. 2021) or other methods (Kuiper and Cui 2021) to quantify the environmental effect of grain loss at different points in the supply chain or in a certain country (García-Herrero et al. 2021). However, they did not take APE and PHLG subsidy strategies into consideration.

To sum up, the current research is deficient in the following aspects. Few researchers have studied the related subsidy policies on the basis of the supply chain members' degree of effort towards reduction losses and emissions. Few researchers explored the effects of the grain reduction subsidies and EISs on supply chain members' incomes on the basis of game theory. Few researchers have considered PHLG to explore the combined effects of APE and PHLG subsidies on the returns of supply chain members.

To resolve these questions, we took as our research subject a grain supply chain consisting of a producer, a retailer and the government. We modified the demand function by considering supply chain members' efforts concerning APE and PHLG reduction. We then proposed and analysed four subsidy and investment models based on the government's subsidy behaviours and supply chain members' investment behaviours in APE and PHLG reduction.

This study has three contributions:

i) We proposed the concept of reducing the level of PHLG and its related equations to reflect the reduction efforts of supply chain members. Because the data related to the costs of grain loss reduction were more complete, we used the cost of grain quantity reduction to reflect the input of PHLG technology.

ii) We revised the market demand by considering the effects of the maximum APE allowed and the supply chain members' PHLG reduction effort on grain quantity loss.

iii) We proposed four investment and subsidy models for APE and PHLG reduction technology and then analysed the investment subsidy rules in different models.

MATERIAL AND METHODS

The No. 1 central document of the Central Committee of the Communist Party of China and the State Council proposed promoting the reduction of losses in the grain supply chain; stabilising the grain subsidies scale; and reducing grain loss in production, storage, consumption and other links. At the same time, promoting green agricultural development includes managing agricultural waste, preventing soil pollution and establishing an environmental monitoring system (State Council the PRC 2023). On the basis of these concepts, there are four models for the government's subsidy policy.

NEL: the supply chain members will not invest in environmental innovation technology and reduction loss technology.

ENL: the producer will invest in environmental innovation technology, and the government will subsidise the investment.

EL: the producer will invest in environmental innovation technology and reduction loss technology, and the government will subsidise the producer.

ELB: on the basis of the *EL* model, the retailer will also adopt reduction loss technology, and the government will subsidise the supply chain members' investment.

Variable descriptions can be found in Table 1 and below. e_0: the unit APE of grain producer. γ: the degree

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of effect of pollution on APE reduction. δ: the sensitivity to pollution emissions factor of consumers. β: the government yield subsidies. *s*: the environmental innovation subsidy coefficient. s_1: the reduction loss subsidy coefficient for the producer. s_2: the reduction loss subsidy coefficient for the retailer. α_1: the quantity attenuation factor of grain in the producer. α_2: the quantity attenuation factor of grain in the retailer. *k*: the cost factor for pollution control. k_1: the cost coefficient for loss reduction for the producer. k_2: the cost coefficient for loss reduction for the retailer. λ: the post-harvest loss rate from the producer. λ_1: the post-harvest loss rate from the retailer. *m*: the producer loss per unit before adopting the loss reduction technology. m_1: the retailer loss per unit before adopting the loss reduction technology. *M*: it is a constant and indicates the maximum value of the allowable APE. p_1: the wholesale price of grain. p_2: the retail price of grain.

Table 1. Variable descriptions

Variable	Description
e_0	unit APE of grain producer
γ	degree of effetct of pollution on APE reduction
δ	sensitivity to pollution emissions factor of consumers
β	government yield subsidies
s	environmental innovation sudsidy coefficient
s_1	reduction loss subsidy coefficient for the producer
s_2	reduction loss subsidy coefficient for the retailer
α_1	quantity attenuation factor of grain in the producer
α_2	quantity attenuation factor of grain in the retailer
k	cost factor for pollution control
k_1	cost coefficient for loss reduction for the producer
k_2	cost coefficient for loss reduction for the retailer
λ	post-harvest loss rate from the producer
λ_1	post-harvest loss rate from the retailer
m	producer loss per unit before adopting the loss reduction technology
m_1	retailer loss per unit before adopting the loss reduction technology
i	i = {NEL, ENL, EL, ELB}
M	constant indicating the maximum value of the allowable APE
p_1	wholesale price of grain
p_2	retail price of grain

APE – agricultural pollution emission; NEL – no subsidy model; ENL – subsidy model 1; EL – subsidy model 2; ELB – subsidy model 3

Source: Author's own elaboration

Problem description

i) We assumed that before adopting environmental innovation investment, the unit of pollution emission of the grain producer is e_0. The final pollution emission after investing in environmental innovation is γe_0, the emission reduction Δe is $(1-\gamma)e_0$ and the degree of pollution emission reduction is $\Delta e / e_0 = [e_0 - (1-\gamma)e_0] / e_0 = \gamma$.

ii) Similar to Liu (2019), we assumed that the relationship between the cost of pollution reduction and the degree of pollution reduction is a quadratic relationship, the cost of pollution reduction is $C = k\gamma^2 / 2$ and the cost coefficient of pollution abatement is *k*.

iii) Before adopting the reduction loss technology, the postharvest loss rate of the producer is λ; after adopting the reduction loss technology, it is $\alpha_1\lambda$. We assumed that the unit loss of the producer before adopting the reduction loss technology is *m*. After adopting the reduction loss technology, it is $\alpha_1\lambda m$, and the level of reduction loss is $(m - \alpha_1\lambda m) / m = 1 - \alpha_1\lambda$. The cost of the reduction loss is $c_1 = \kappa_1(1-\alpha_1\lambda)^2 / 2$. We assumed that the postharvest loss rate of the retailer is λ_1; after adopting the reduction loss technology, it is $\alpha_2\lambda_1$. We assumed that the unit loss of the retailer before adopting the reduction loss technology is m_1. After adopting the reduction loss technology, it is $\alpha_2\lambda_1 m_1$, and the level of reduction loss is $(m_1 - \alpha_2\lambda_1 m_1) / m = 1 - \alpha_2\lambda_1$. The cost of the reduction loss is $c_2 = \kappa_2(1-\alpha_2\lambda_1)^2 / 2$.

iv) Similar to Zhang et al. (2021), we assumed that the demand formula is $D^i = M - \delta\gamma e_0 - p_{2i}$. *M* is a constant and indicates the maximum value of pollution emission. δ indicates the sensitivity coefficient of consumers to pollution emission. p_{1i} and p_{2i} indicate the wholesale price of grain and the retail price of grain in the *i* model *i* = {*NEL*, *ENL*, *EL*, *ELB*}.

v) We assumed that the government will offer a subsidy to share the environmental innovation investment of the producer; similar to the research of Zhang et al. (2021), the subsidy coefficient is *s*. In addition, to stimulate the producer and the retailer to reduce the postharvest loss, the government will offer a subsidy with subsidy coefficients s_1 and s_2.

vi) Consumer surplus is an important indicator of consumer welfare; for the government, it is an important indicator to pay attention to:

$$CS = \int_{p_i}^{p_{mas}} D_i dp = \frac{D_i^2}{2} \tag{1}$$

where: p_{max} – price when the market demand equals zero; $p_{max} = M - \delta e_0$.

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Subsidy strategy analysis

In the NEL model, revenue functions of the grain producer and the government are addressed in Appendix A1 in the ESM, and the relevant optimal decisions are as follows:

$$\begin{cases} p_1^{NEL^*} = \dfrac{M-\beta+c-\delta e_0}{2} \\ p_2^{NEL^*} = \dfrac{3M-\beta+c-3\delta e_0}{4} \\ D^{NEL^*} = \dfrac{M+\beta-c-\delta e_0}{4} \end{cases} \quad (2)$$

$$\begin{cases} \pi_p^{NEL^*} = \dfrac{-(\lambda-1)(M+\beta-c-\delta e_0)^2}{8} \\ \pi_r^{NEL^*} = \dfrac{(\lambda-1)(\lambda_1-1)(M+\beta-c-\delta e_0)^2}{16} \\ \pi_g^{NEL^*} = \dfrac{\left[1-2(\lambda_1+1)(\lambda-1)\right](M+\beta-c-\delta e_0)^2}{32} - \\ \quad - \dfrac{\beta(M+\beta-c-\delta e_0)}{4} \end{cases}$$

In the ENL model, revenue functions are addressed in Appendix A2 in the ESM, and the relevant optimal decisions are as follows:

$$\begin{cases} p_1^{ENL^*} = \dfrac{M-\beta+c-\delta e_0\gamma}{2} \\ p_2^{ENL^*} = \dfrac{3M-\beta+c-3\delta e_0\gamma}{4} \\ D^{ENL^*} = \dfrac{M+\beta-c-\delta e_0\gamma}{4} \end{cases} \quad (3)$$

$$\begin{cases} \pi_p^{ENL^*} = \dfrac{k\gamma^2(s-1)}{2} - \dfrac{(\lambda-1)A}{8} \\ \pi_r^{ENL^*} = \dfrac{(\lambda-1)(\lambda_1-1)A}{16} \\ \pi_g^{ENL^*} = \dfrac{\left[1+2(1-\lambda)(3-\lambda_1)\right]A}{32} - \\ \quad - \dfrac{\beta(M+\beta-c-\delta e_0\gamma)}{4} - \dfrac{k\gamma^2}{2} \end{cases}$$

Here, $A = (M + \beta - c - \delta e0\gamma)^2$.

Inference 1

i) $\dfrac{\partial p_1^{ENL^*}}{\partial s} = 0$, $\dfrac{\partial p_2^{ENL^*}}{\partial s} = 0$, $\dfrac{\partial \pi_p^{ENL^*}}{\partial s} > 0$,

$$\frac{\partial \pi_r^{ENL^*}}{\partial s} = 0, \ \frac{\partial \pi_g^{ENL^*}}{\partial s} = 0 \quad (4)$$

ii) $$\frac{\partial p_1^{ENL^*}}{\partial \gamma} < 0, \ \frac{\partial p_2^{ENL^*}}{\partial \gamma} < 0, \ \frac{\partial \pi_p^{ENL^*}}{\partial \gamma} < 0, \quad (5)$$

$$\frac{\partial \pi_r^{ENL^*}}{\partial \gamma} < 0, \ \frac{\partial \pi_g^{ENL^*}}{\partial \gamma} < 0 \quad (5)$$

The analytical procedure is described in Appendix B in the ESM.

From Equation (4), it is clear that the EIS coefficient *s* does not affect the equilibrium prices trend and the revenue of the retailer and the government, but it affects the producer's revenue. At the same time, the producer benefits will increase as the EIS coefficient increases because the EIS will subsidise the producer's environmental innovation investment. Therefore, the EIS does not affect the retailer's revenue, but the producer's revenue will decrease. The government's revenue is composed of the supply chain members' revenues, consumer surplus (CSs) and associated subsidy expenditures. This result is similar to that of Zhang et al. (2021); however, they did not analyse the relationships among the EIS coefficient, prices and the benefits of other supply chain members.

From Equation (5), it is clear that the price will decrease as the producer's degree of effort towards APE reduction increases. We can infer that the trend of the wholesale price is smaller than the retail price caused by the degree of change in the producer's APE reduction effort. This change is because the producer promotes the level of effort towards emission reduction, which increases costs for environmental innovation, so the producer must set a higher price and then the retailer also must. In addition, the supply chain members' revenues will decrease with the increase in the level of the producer's emission reduction effort. Under certain conditions, the producer that improves its level of APE reduction will help it obtain more revenue, but the wholesale price will decrease, which has a negative correlation with the producer's revenue. The government subsidies for the producer's environmental innovation investments may not pay for themselves, and the CS cannot compensate for the revenue lack of other supply chain members, achieving negative revenue growth.

In the EL model, revenue functions are addressed in Appendix A3 in the ESM, and the relevant optimal decisions are as follows:

$$\begin{cases} p_1^{EL^*} = \dfrac{M-\beta+c-\delta e_0\gamma}{2} \\ p_2^{EL^*} = \dfrac{3M-\beta+c-3\delta e_0\gamma}{4} \\ D^{EL^*} = \dfrac{M+\beta-c-\delta e_0\gamma}{4} \end{cases} \quad (6)$$

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$$\begin{cases} \pi_p^{EL^*} = \dfrac{k\gamma^2(s-1)+k_1(\alpha_1\lambda-1)^2(s_1-1)}{2} - \dfrac{(\alpha_1\lambda-1)A}{8} \\ \pi_r^{EL^*} = \dfrac{(\alpha_1\lambda-1)(\lambda_1-1)A}{16} \\ \pi_g^{EL^*} = \dfrac{\left[1-4(\alpha_1\lambda-1)+2(\alpha_1\lambda-1)(\lambda_1-1)\right]A}{32} - \\ \quad - \dfrac{k\gamma^2+k_1(\alpha_1\lambda-1)^2}{2} - \dfrac{\beta(M+\beta-c-\delta e_0\gamma)}{4} \end{cases} \tag{6}$$

Inference 2

$$i)\ \frac{\partial p_1^{EL^*}}{\partial s}=0,\ \frac{\partial p_2^{EL^*}}{\partial s}=0,\ \frac{\partial \pi_p^{EL^*}}{\partial s}>0,\ \frac{\partial \pi_r^{EL^*}}{\partial s}=0,\ \frac{\partial \pi_g^{EL^*}}{\partial s}=0 \tag{7}$$

$$ii)\ \frac{\partial p_1^{EL^*}}{\partial \gamma}<0,\ \frac{\partial p_2^{EL^*}}{\partial \gamma}<0,\ \frac{\partial \pi_p^{EL^*}}{\partial \gamma}<0,\ \frac{\partial \pi_r^{EL^*}}{\partial \gamma}<0,\ \frac{\partial \pi_g^{EL^*}}{\partial \gamma}<0 \tag{8}$$

$$iii)\ \frac{\partial p_1^{EL^*}}{\partial s_1}=0,\ \frac{\partial p_2^{EL^*}}{\partial s_1}=0,\ \frac{\partial \pi_p^{EL^*}}{\partial s_1}>0,\ \frac{\partial \pi_r^{EL^*}}{\partial s_1}=0,\ \frac{\partial \pi_g^{EL^*}}{\partial s_1}=0 \tag{9}$$

$$iv)\ \frac{\partial p_1^{EL^*}}{\partial \alpha_1}=0,\ \frac{\partial p_2^{EL^*}}{\partial \alpha_1}=0,\ \frac{\partial \pi_p^{EL^*}}{\partial \alpha_1}<0,\ \frac{\partial \pi_r^{EL^*}}{\partial \alpha_1}<0,\ \frac{\partial \pi_g^{EL^*}}{\partial \alpha_1}>0 \tag{10}$$

From Equations (4) and (7) in Inferences 1 and 2, the variation trend of the decision variables and the dependent variables is consistent with the variation trend of the EIS coefficient in the EL and ENL models. At the same time, the producer's revenue increases with the growth of EIS coefficient *s*, and the producer's changing range is certain in both models. This finding suggests that, for the producer, the trend of the change in the decision variable and the dependent variable with the EIS coefficient is not affected by the investment in PHLG technology.

From Equations (5) and (8) in Inferences 1 and 2, as the producer's effort to reduce APE increases, the trend of the decision variable and the dependent variable in the EL and ENL models aligns accordingly. In both the EL and ENL models, as producers increased the investment in APE technology, both wholesale and retail prices decreased. However, in both models, the magnitude of changes in the benefits for supply chain members were different as the producer's degree of effort towards APE reduction increased. This finding indicates that changes in supply chain members' revenues will be affected by the increase in the producer's degree of effort towards APE reduction.

From Equation (9), it is clear that reducing subsidy coefficient s_1 does not affect the trends of the equilibrium prices and the revenues of the retailer and the government, but it does affect the producer's revenue. At the same time, the producer's revenue will increase because of the increase in subsidy reduction factor s_1. This revenue increase is possible because the reduction subsidy is to subsidise the producer's APE reduction inputs, which is not related to the retailer's benefit, and the producer's revenue will increase. The government's revenue is composed of the revenues of other supply chain members, CSs and the related subsidy expenditures. The combination of these revenues and expenditures offsets the effect of reducing the subsidy coefficient on the government's revenue when investing in PHLG.

From Equation (10), the quantity attenuation coefficient of grain for producer α_1 is not related to the decision variables and is negatively related to the dependent variables $\pi_p^{EL^*}$ and $\pi_r^{EL^*}$, and positively related to the dependent variable $\pi_g^{EL^*}$. If the quantity attenuation coefficient of grain for producer α_1 is increasing, then the per-unit loss of quantity is increasing. If the quantity attenuation coefficient of grain for producer α_1 is decreasing, then the per-unit loss of quantity is decreasing. In essence, to maximise revenue generation across the supply chain, it is crucial for the producer to leverage technological advancements fully.

In the ELB model, revenue functions are addressed in Appendix A4 in the ESM, and the relevant optimal decisions are as follows:

$$\begin{cases} p_1^{ELB^*} = \dfrac{M-\beta+c-\delta e_0\gamma}{2} \\ p_2^{ELB^*} = \dfrac{3M-\beta+c-3\delta e_0\gamma}{4} \\ D^{ELB^*} = \dfrac{M+\beta-c-\delta e_0\gamma}{4} \end{cases}$$

$$\begin{cases} \pi_p^{ELB^*} = \dfrac{(s-1)k\gamma^2+(s_1-1)k_1(\alpha_1\lambda-1)^2}{2} - \dfrac{(\alpha_1\lambda-1)A}{8} \\ \pi_r^{ELB^*} = \dfrac{(\alpha_1\lambda-1)(\alpha_2\lambda_1-1)A}{16} + \dfrac{k_2(\alpha_2\lambda_1-1)^2(s_2-1)}{2} \\ \pi_g^{ELB^*} = \dfrac{\left[5+2(\alpha_1\lambda-1)(\alpha_2\lambda_1-1)-4\alpha_1\lambda\right]A}{32} - \\ \quad - \dfrac{\beta(M+\beta-c-\delta e_0\gamma)}{4} - \\ \quad - \dfrac{k_1(\alpha_1\lambda-1)^2+k_2(\alpha_2\lambda_1-1)^2+k\gamma^2}{2} \end{cases} \tag{11}$$

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Inference 3

$$i)\ \frac{\partial p_1^{ELB*}}{\partial s}=0,\ \frac{\partial p_2^{ELB*}}{\partial s}=0,\ \frac{\partial \pi_p^{ELB*}}{\partial s}>0,\ \frac{\partial \pi_r^{ELB*}}{\partial s}=0,\ \frac{\partial \pi_g^{ELB*}}{\partial s}=0 \tag{12}$$

$$ii)\ \frac{\partial p_1^{ELB*}}{\partial \gamma}<0,\ \frac{\partial p_2^{ELB*}}{\partial \gamma}<0,\ \frac{\partial \pi_p^{ELB*}}{\partial \gamma}<0,\ \frac{\partial \pi_r^{ELB*}}{\partial \gamma}<0,\ \frac{\partial \pi_g^{ELB*}}{\partial \gamma}<0 \tag{13}$$

$$iii)\ \frac{\partial p_1^{ELB*}}{\partial s_1}=0,\ \frac{\partial p_2^{ELB*}}{\partial s_1}=0,\ \frac{\partial \pi_p^{ELB*}}{\partial s_1}>0,\ \frac{\partial \pi_r^{ELB*}}{\partial s_1}=0,\ \frac{\partial \pi_g^{ELB*}}{\partial s_1}=0 \tag{14}$$

$$iv)\ \frac{\partial p_1^{ELB*}}{\partial s_2}=0,\ \frac{\partial p_2^{ELB*}}{\partial s_2}=0,\ \frac{\partial \pi_p^{ELB*}}{\partial s_2}=0,\ \frac{\partial \pi_r^{ELB*}}{\partial s_2}>0,\ \frac{\partial \pi_g^{ELB*}}{\partial s_2}=0 \tag{15}$$

$$v)\ \frac{\partial p_1^{ELB*}}{\partial \alpha_1}=0,\ \frac{\partial p_2^{ELB*}}{\partial \alpha_1}=0,\ \frac{\partial \pi_p^{ELB*}}{\partial \alpha_1}<0,\ \frac{\partial \pi_r^{ELB*}}{\partial \alpha_1}<0,\ \frac{\partial \pi_g^{ELB*}}{\partial \alpha_1}<0 \tag{16}$$

$$vi)\ \frac{\partial p_1^{ELB*}}{\partial \alpha_2}=0,\ \frac{\partial p_2^{ELB*}}{\partial \alpha_2}=0,\ \frac{\partial \pi_p^{ELB*}}{\partial \alpha_2}=0,\ \frac{\partial \pi_r^{ELB*}}{\partial \alpha_2}<0,\ \frac{\partial \pi_g^{ELB*}}{\partial \alpha_2}<0 \tag{17}$$

From Equations (4), (7) and (12) in Inferences 1, 2 and 3, as EIS coefficient s increases, the decision variables and the dependent variables exhibit a corresponding trend. At the same time, as EIS coefficient s increases, the producer's revenue also increases, and the changing range is the same in all three models. This finding suggests that, for the producer, the change trends of the decision variables and the dependent variables with the increase in the EIS coefficient are not affected by the behaviours of supply chain members in APE reduction investment.

From Equations (5), (8) and (13) in Inferences 1, 2 and 3, as the producer's effort to reduce APE increases, the decision variables and the dependent variables show a similar pattern of change. At the same time, with the changes in the producer's degree of effort towards APE reduction, it is clear that the patterns of change regarding wholesale and retail prices are the same. When the producer increases its effort to reduce APE, the change in the equilibrium prices will not be influenced by the decrease in the producer's investment in APE reduction technology. However, the magnitude of revenue changes for other supply chain members differs as the producer's degree of effort towards APE reduction increases.

From Equations (9) and (14) in Inferences 2 and 3, we can infer that reducing subsidy coefficient s_1 will not affect the trends of equilibrium prices or the benefits of the retailer and the government, but it will influence the producer's income. At the same time, as the reduction value of the subsidy coefficient increases, the producer benefit will increase. This finding indicates that, as the subsidy reduction coefficient increases, the trend and magnitude of changes in equilibrium prices and revenues for the retailer and the government will not be influenced by the retailer's investment behaviour in loss reduction technology. However, the magnitude of changes in the producer's benefits will be affected by the retailer's investment decisions.

From Equation (15), the government separately subsidises the costs of investment in loss reduction technology of the producer and the retailer, and the reduction of the subsidy coefficient will not affect the changing trend for the equilibrium prices and the benefits of the producer and the government, but it will affect the retailer's revenue. The government benefit consists of the benefits from other supply chain members, the CSs and the associated subsidy expenditures. The loss reduction subsidy coefficient's influence on the government's revenue was eliminated after mixing the incomings and outgoings.

From Equation (10) in Inference 2 and Equation (16) in Inference 3, the quantity attenuation coefficient of grain for producer α_1 is not correlated with the decision variables and is negatively correlated with the dependent variables. In terms of the government's revenue, the EL and ELB models produce an opposite result. The government's subsidy for the producer's grain quantity attenuation coefficient α_1 cannot offset the inputs to the producer. In the EL and ELB models, the correlation between the government's revenue and the grain quantity attenuation coefficient is opposite, whereas the retailer's revenue is only negative because the trend and magnitude of changes for the equilibrium prices with the increase in the quantity attenuation coefficient for the producer will not be affected by the retailer's investment behaviour for the investment in reduction loss technology. However, the magnitude

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of changes for supply chain members' incomes are affected by the retailer's investment behaviour.

From Equation (17), the quantity attenuation coefficient of grain for retailer α_2 is not correlated with the decision variable $\pi_p^{ELB^*}$ and negatively correlated with the dependent variables $\pi_r^{ELB^*}$ and $\pi_g^{ELB^*}$ because the larger the quantity attenuation coefficient of grain for retailer α_2, the greater the per-unit loss of quantity is. The smaller the quantity attenuation coefficient of the grain for retailer α_2, the greater the improvement rate of the retailer's unit quantity loss is and the smaller the unit quantity loss is. Therefore, the retailer should make full use of the loss reduction technology if supply chain members want to achieve greater revenues.

Inference 4

When the conditions $1 \geq s \geq \psi_1$, $C(\gamma) < \psi_2$ are met, it is feasible for the producer to invest in APE reduction technology and the government to subsidise that investment (see Appendix C1 in the ESM).

If we know $s > \psi_1$, when $0.83 < \gamma \leq 1$, we can know when the government should provide a higher EIS factor s to the producer. Otherwise, the producer will refuse to use APE reduction technologies because of the input-output imbalance. When $0 \leq \gamma < 0.83$, the government is able to provide the producer a lower subsidy coefficient s for its environmental innovation inputs. However, if the cost of APE reduction technology is high, it will not be appropriate for the government to provide subsidies to the producer. In this situation, the government may provide a fixed cost subsidy to the producer or set a ceiling on the subsidy.

Therefore, when the cost of APE reduction technology $C(\gamma)$ and the EIS factor s are within a certain range, the producer will invest in APE reduction technology and the government will subsidise it. Otherwise, the government will provide only a fixed cost subsidy.

Inference 5

When $s_1 > \zeta_1$, $C(\alpha_1, \lambda) < \zeta_2$, it is feasible for the producer to invest in APE and PHLG reduction technologies and for the government to subsidise them.

If we know $s_1 > \zeta_1 = 1 + A\lambda(\alpha_1 - 1) / 4k_1(\alpha_1\lambda - 1)^2$, as the postharvest loss rate of producer λ increases, the loss reduction subsidy coefficient for producer s_1 also increases. In addition, if $\lambda \leq 1 / (2 - \alpha_1)$, the loss reduction subsidy coefficient for producer s_1 increases as the quantity of grain decays for producer α_1. In addition, if the costs of the PHLG reduction technology are high, it will not be appropriate for the government to provide PHLG reduction subsidies to the producer. Instead, the government can provide subsidies to the producer for APE reduction technology.

Therefore, when the costs of PHLG reduction technology of the producer and the related subsidy factor are within a certain range, the producer will invest in APE and PHLG technologies, and the government will subsidise them. Otherwise, the government will provide only the APE technology subsidy to the producer.

Inference 6

When $s_2 > \phi_1$, $C(\alpha_2, \lambda_1) < \phi_2$, it is feasible for the retailer to invest in PHLG reduction technology and the government to subsidise it (see Appendix C3 in the ESM).

If we know $s_2 > \phi_1 = 1 + A\lambda_1(\alpha_1\lambda - 1)(1 - \alpha_2) / 8k_2(\alpha_1\lambda_1 - 1)^2$, we can obtain that when the producer's postharvest loss rate λ_1 increases, the loss reduction subsidy factor for retailer s_2 will decrease. When $A\lambda_1(\alpha_2 - 1)(\alpha_1\lambda - 1) / 16 > k_2(\alpha_2\lambda - 1)^2 / 2$, as the quantity attenuation factor of grain for retailer α_2 increases, the loss reduction subsidy factor for retailer s_2 will increase. As the postharvest loss rate for retailer λ_1 and the quantity attenuation factor of grain for retailer α_2 increase, the situation does not always enable the government to provide a higher reduction subsidy, and the government will provide the subsidy only if certain conditions are met. In addition, if the cost of the technology to reduce global greenhouse gas emissions is high, it will not be appropriate for the government to provide a subsidy to the retailer. In this situation, the government may not provide a technology subsidy to the retailer.

Therefore, when the costs of PHLG reduction technology for the retailer and the subsidy for that technology are within a certain range, the retailer will invest in PHLG reduction technology, and the government will subsidise this investment. Otherwise, the government will not be able to subsidise the retailer but maybe subsidise the producer.

RESULTS AND DISCUSSION

Case description. To verify the validity and reliability of the model constructed in this article, we conducted simulation experiments on the basis of real data related to PHLGs and agricultural pollution in China.

Regarding the setting of APE parameters, the Chinese government indicated in 2022 that agricultural pollutants should include four indicators: nitrogen, ammonia nitrogen, phosphorus and chemical oxygen demand (Ministry of Ecology and Environment the PRC 2022). In this study, we selected phosphorus emissions

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as an indicator of APE. For example, in Anji County in China, the utilisation rate of phosphate fertiliser in wheat cultivation is generally less than 30% (Anji County People's Government 2022). Assuming a phosphate fertiliser utilisation rate of 20%, and based on an average phosphorus application rate of 30–37.5 g/m^2 for wheat, there are approximately 24–30 g of phosphorus emissions per m^2 of land (Farmers' Little 2021) during wheat cultivation in this region. Because the pollutant emission control standards should be higher than the actual emissions by a certain margin (Chow 2011), this study set a maximum allowable value $M = 49$. Based on an average wheat yield of 0.30–0.45 kg/m^2 (Agricultural Planting Network 2024), the phosphorus emission value per unit of wheat output is approximately 0.08 to 0.12. Therefore, in this study, we assumed $e_0 = 0.1$. The level of pollution emissions generally ranged from 0 to 1, so this study assumed $\gamma = 0.1$. When constructing a consumer utility function, Chen et al. (2017) introduced a coefficient reflecting the consumers' sensitivity to environmental pollution, with a special value range (≥ 0). Therefore, in this case study, we set this coefficient as $\delta = 0.6$. In addition, Zhang et al. (2021) indicated that the government subsidy coefficient for environmental innovation should fluctuate within a certain range [0, 1]; in the case simulation, we set this coefficient to 0.3. According to the subsidy rules for agricultural production issued by Pudong New Area, Shanghai, China, in 2023 (Pudong New Area Agriculture and Rural Affairs Committee, Pudong New Area Finance Bureau 2023), the subsidy coefficient for fertilisers and pesticides should be set at a specific value [0.25, 0.75]. On this basis, in this study, we set the government subsidy coefficient as $s = 0.4$ for environmental innovation by producers.

Regarding the setting of PHLG parameters, Zhang et al. (2021) suggested in their research that the government's output subsidy coefficient should be within a specific range [0, 1]. However, according to the 'Incentive Measures for Major Grain-Producing Counties' issued by the government in 2018 (Ministry of Finance of the People's Republic of China 2018), the weighting proportions of the four evaluation indicators (grain commodity volume, grain output, sown area and performance) were clarified, with grain output accounting for a 20% weight. The specific subsidy coefficients are as follows: 0.2 for Class I regions (Zhejiang, Guangdong), 0.5 for Class II regions (Liaoning, Jiangsu, Fujian, Shandong) and 1 for Class III regions (excluding Class I and II regions, Beijing, Shanghai, Tianjin). Therefore, the subsidy coefficient for grain output is further clarified [0.04, 0.2]. On the basis of relevant policies, in this study, we set the government subsidy coefficient for grain output as $\beta = 0.06$. The formula for calculating the grain loss rate is the natural loss divided by the total production. On the basis of previous field investigations in major grain-producing areas in China, we found that regardless of the size of farmer households, the grain loss rate ranged from 10% to 20%. This result is the same as data published by the Chinese Ministry of Agriculture in 2012, which reported a PHLG rate of 7% to 11% (Ministry of Agriculture of the People's Republic of China 2012). In light of this finding, we set the postharvest loss rate for producers as $\lambda = 0.1$. According to Li et al. (2020), the use of loss reduction technologies can reduce the grain loss rate for producers by approximately 2.5%. Based on this estimation, the theoretical attenuation coefficient for the number of producers after adopting loss reduction technologies should be within (0, 0.77). In this study, we set it as $\alpha_1 = 0.1$. In addition, according to the research findings of Liu et al. (2023), retailers experience a quantity loss rate of approximately 3% to 8% before adopting loss reduction technologies. However, after implementing these technologies, their quantity loss rate decreases to less than 1%. Therefore, we set the postharvest loss rate for retailers as $\lambda_1 = 0.04$. Furthermore, considering that the attenuation coefficient for the number of retailers after adopting loss reduction technologies is within the range of (0, 0.33), we set this coefficient as $\alpha_2 = 0.05$. Moreover, government subsidy coefficients for supply chain members' freshness preservation measures typically are within the range of [0, 1]. In their study on the fresh food supply chain, He and Yang (2023) set this subsidy coefficient as [0.1, 0.4]. Therefore, in the context of the grain supply chain, we established a subsidy coefficient for both producers and retailers that aligns with practical considerations and is guided by theoretical principles, set as $s_1 = 0.1$, $s_2 = 0.3$.

In addition, during our analysis of the results, when parameters γ, s, s_1, s_2, α_1, α_2 are considered as independent variables, their values are not single specific numbers but vary continuously within the range of 0 to 1. This finding implies that we are exploring the effect of different values of these parameters on the results across their entire valid range of 0 to 1.

Result analysis. On the basis of the specific descriptions of the parameters in the chapter Case description, we conducted a case simulation analysis of the actual situation by using MATLAB software.

The grain prices decreased as the reduction effort increased. At the same time, as the producer's effort to re-

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duce APE changed, the trend in the wholesale price was smaller than the retail price. In addition, as the producer's effort in reducing APE increased, the supply chain members' revenues decreased. Therefore, if the government wants to produce better social benefits, it should encourage the producer to explore the best environmental innovation technology for the level of APE.

Comparing Figures 1–3 shows that as the EIS coefficient increases, the decision variables and the dependent variables exhibit a corresponding trend under the ENL and EL models. This finding suggests that, for the producer, the trends in the decision variables and the dependent variables are not affected by investing in PHLG reduction technology.

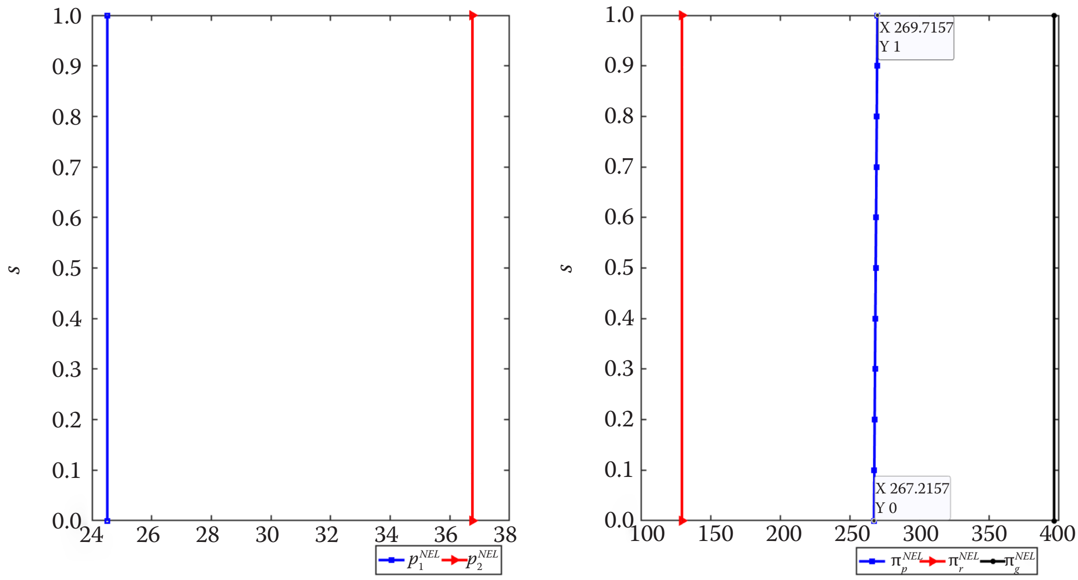

Figure 1. Variation tendencies in the NEL model

NEL – no subsidy model; s – environmental innovation subsidy coefficient; p – price; π – revenue
Source: Author's own elaboration

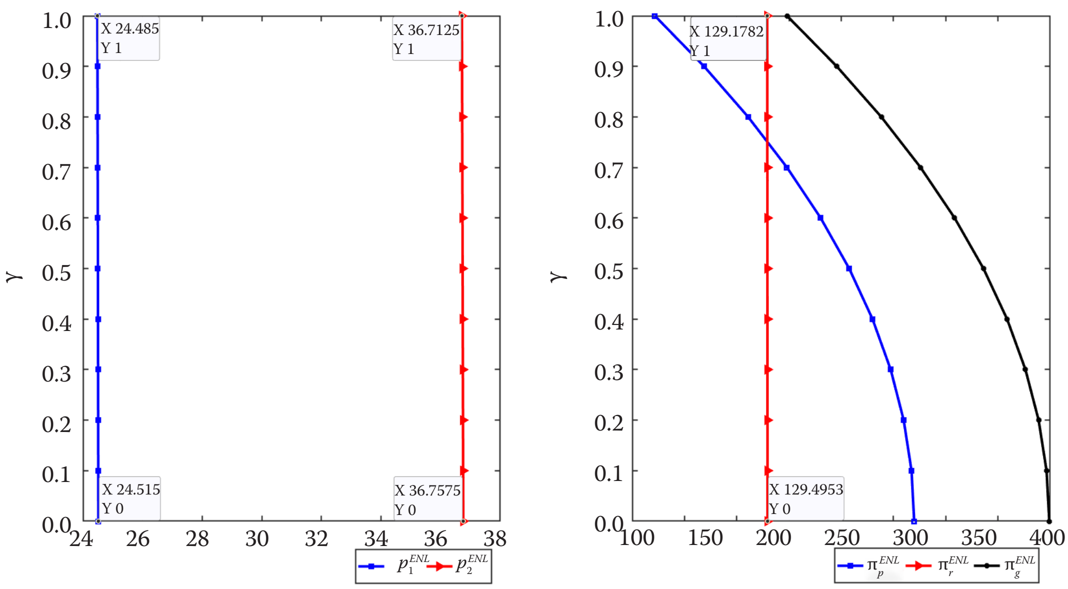

Figure 2. Variation tendencies in the ENL model

ENL – subsidy model 1; γ – degree of effect of pollution on agricultural pollution emission reduction; p – price; π – revenue
Source: Author's own elaboration

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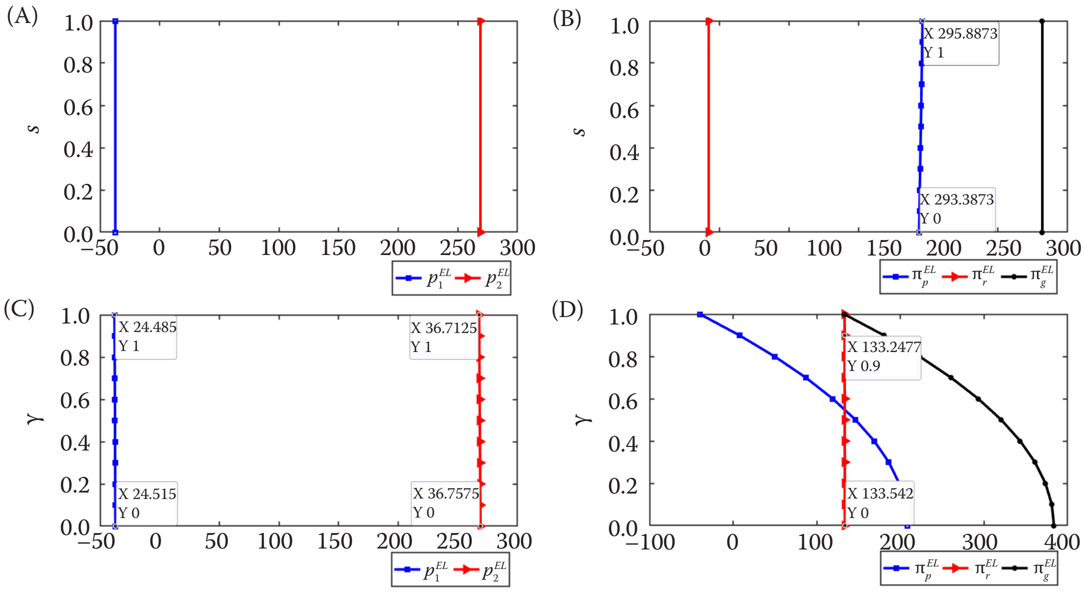

Figure 3. Variation tendencies with γ and *s* in the EL model

γ –degree of pollution on agricultural pollution emission reduction; *s* – environmental innovation subsidy coefficient; EL – subsidy model 2; *p* – price; π – benefit

Source: Author's own elaboration

Moreover, as the producer's degree of effort towards APE reduction increased, in the EL and ENL models, the decision variables and the dependent variables had the same trend. In both models, the magnitude of change in supply chain members' returns was different as the producer's degree of effort towards APE reduction increased. Therefore, the magnitude of change in supply chain members' returns were affected by the

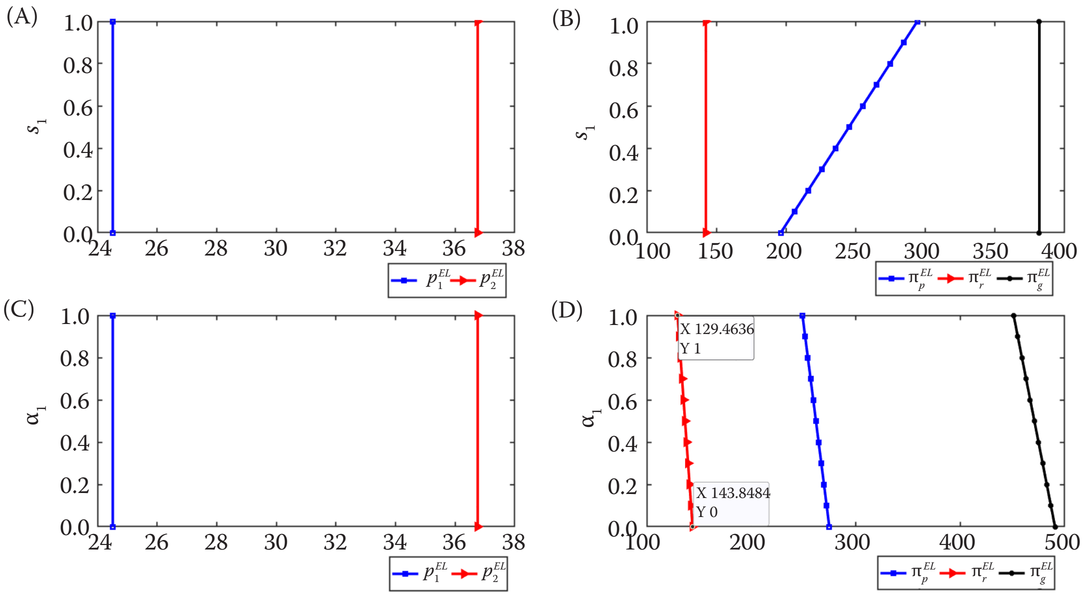

Figure 4. Variation tendencies with s_1 and α_1 in the EL model

s_1 – reduction loss subsidy coefficient for the producer; α_1 – quantity attenuation factor of grain in the producer; EL – subsidy model 2; *p* – price; π – benefit

Source: Author's own elaboration

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producer's investment in APE reduction technology as the producer's effort increased.

According to Figure 4, PHLG reduction subsidy coefficient s_1 did not affect the trends of equilibrium prices, and the retailer and the government benefited, but it affected the producer's benefit. At the same time, as PHLG reduction subsidy coefficient s_1 increased, the producer's revenue increased, and the producer PHLG reduction subsidy stimulated the producer to adopt PHLG reduction technology. In addition, the producer's quantity attenuation coefficient of grain α_1 was not related to the decision variables, negatively related to the dependent variables $\pi_p^{EL^*}$ and $\pi_r^{EL^*}$, and positively related to the dependent variable $\pi_g^{EL^*}$. Thus, to maximise their benefits, supply chain members can adjust strategically for the most optimal degree of loss reduction on the basis of the prevailing benefit trends.

Comparing Figures 1–5, in the EL, ELB and ENL models, shows that as the EIS coefficient and the producer's APE reduction effort increased, the decision variables and the dependent variables had the same trend.

Moreover, comparing Figures 4 and 5, in the EL and ELB models, shows that coefficient of derogation subsidy s_1 did not affect the change trend of equilibrium prices and benefits of the retailer and the government. Surprisingly, this coefficient affects the producer's benefit positively. This finding indicates that, as the reduction of PHLG subsidy coefficient s_1 for the producer increased, the trends and change scales for the equilibrium prices and the benefits for the retailer and the government were not affected by the investment behaviour of the retailer in reduction loss technology, but the magnitude of changes in the producer's benefits was affected by the investment behaviour of the retailer.

Comparing Figures 6A and 6D shows that PHLG reduction subsidy coefficient s_2 had no effect on the equilibrium prices and the producer's revenue. However, it was positively correlated with the retailer's revenue. The loss reduction subsidy coefficient's influence on the government's revenue was eliminated after mixing the incomings and outgoings. Comparing Figures 4 and 6, in the EL and ELB models, shows that the quantity loss reduction coefficient of producer α_1 was not correlated with the decision variables and was negatively correlated with the dependent variables. The government's revenue had an opposite change. Therefore, if the supply chain members want to obtain more benefits, they can adjust the most perfect degree of PHLG reduction according to the benefits trend. In addition, the quantity loss reduction coefficient of retailer α_2 was not correlated with the decision variable $\pi_p^{ELB^*}$ and negatively correlated with the dependent variables $\pi_r^{ELB^*}$ and $\pi_g^{ELB^*}$.

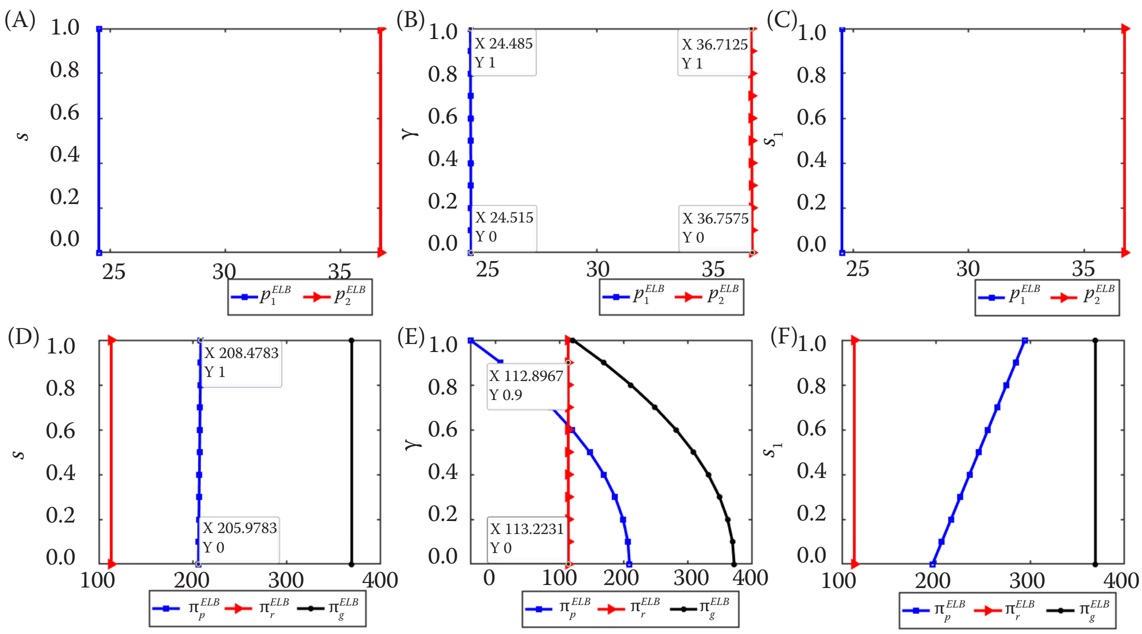

Figure 5. Variation tendencies of equilibrium prices and benefits with s, γ, and s_1 in the ELB model

s – environmental innovation sudsidy coefficient; γ – degree of pollution on APE reduction; s_1 – reduction loss subsidy coefficient for the producer; ELB – subsidy model 3; p – price; π – benefit

Source: Author's own elaboration

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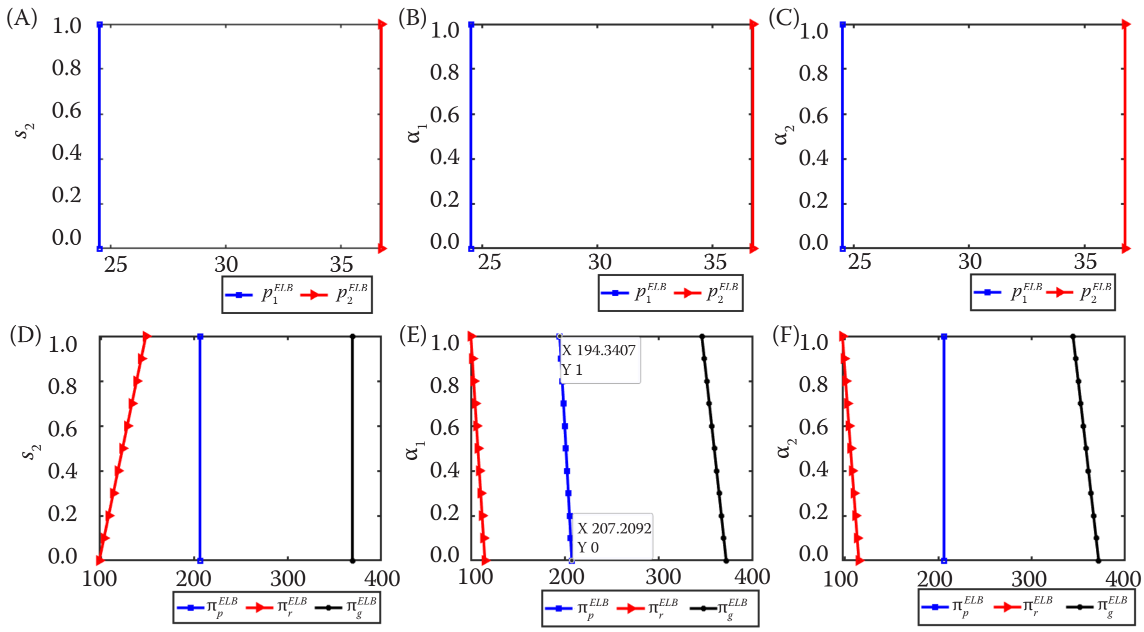

Figure 6. Variation tendencies of equilibrium prices and benefits with s_2, α_1 and α_2 in the ELB model

s_2 – reduction loss subsidy coefficient for the retailer; α_1 – quantity attenuation factor of grain in the producer; α_2 – quantity attenuation factor of grain in the retailer; ELB – subsidy model 3; p – price; π – benefit
Source: Author's own elaboration

To enhance revenue generation among supply chain members, the retailer must optimally leverage PHLG reduction technology.

According to Figure 7, when the costs of APE reduction technology $C(\gamma)$ and EIS factor s were within a certain range, the producer invested in APE reduction technology, and the government subsidised them. If the costs of APE reduction technology exceeded a certain range, the government did not need to subsidise. In Figure 7, the government subsidy behaviour for the producer's APE reduction investments improved the producer's profitability. Simultaneously, the producer must strive towards minimising the costs associated with APE reduction technologies, thereby rendering them more viable for the government subsidies.

Figure 8 indicates that when the cost of PHLG reduction technology and EIS coefficient s_1 were within a certain range, the producer invested in PHLG reduction technologies, with the government providing subsidies. However, if the cost of PHLG reduction technology exceeded a certain threshold $[C(\alpha_1, \lambda) > \zeta_2]$, the government did not provide subsidies. With the government offering subsidies for PHLG reduction technologies to the producer, both parties can benefit: the producer enhances its own efficiency, and the government also gains. For the government to reap greater benefits, the producer should make every effort to minimise the costs associated with PHLG. Only under these circumstances is it feasible for the government to offer subsidies sustainably.

Observing Figure 9, for the retailer, we find that when EIS coefficient s_2 and the cost of PHLG emission reduction technology $C(\alpha_2, \lambda_1)$ were within a certain range $[s_2 > \phi_1, C(\alpha_2, \lambda_1) < \phi_2]$, the retailer adopted PHLG emission reduction technology, and the government provided subsidies. However, if the cost of the PHLG emission reduction technology exceeded a specific threshold $[C(\alpha_2, \lambda_1) > \phi_2]$, the government ceased to subsidise it directly but instead shifted subsidies towards the producer's loss mitigation investments and APE reduction inputs. In summary, the government's subsidies on the retailer's loss mitigation investments can effectively increase the retailer's revenue.

We compared our results with those of other studies and discovered some differences and similarities (An and Ouyang 2016; Chen et al. 2017). In our study, we concluded that the EIS coefficient did not affect the trend of equilibrium prices and returns for the government as well as for the unsubsidised supply chain members, which is different from the findings of Chen et al. (2017) and Zhang et al. (2021). The mathematical

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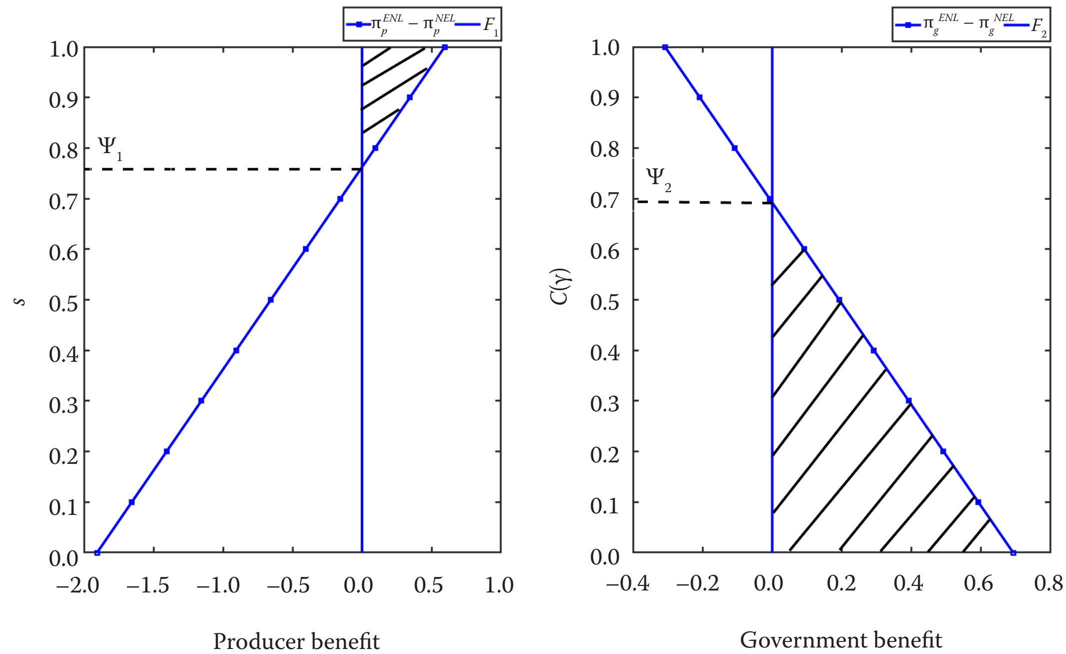

Figure 7. Subsiding situations of APE technology in subsiding and investing

APE – agricultural pollution emission; s – environmental innovation subsidy coefficient; C – costs of APE reduction technology; γ – degree of effect of pollution on APE reduction; ψ – equilibrium solution; π – benefit; F – zero mark
Source: Author's own elaboration

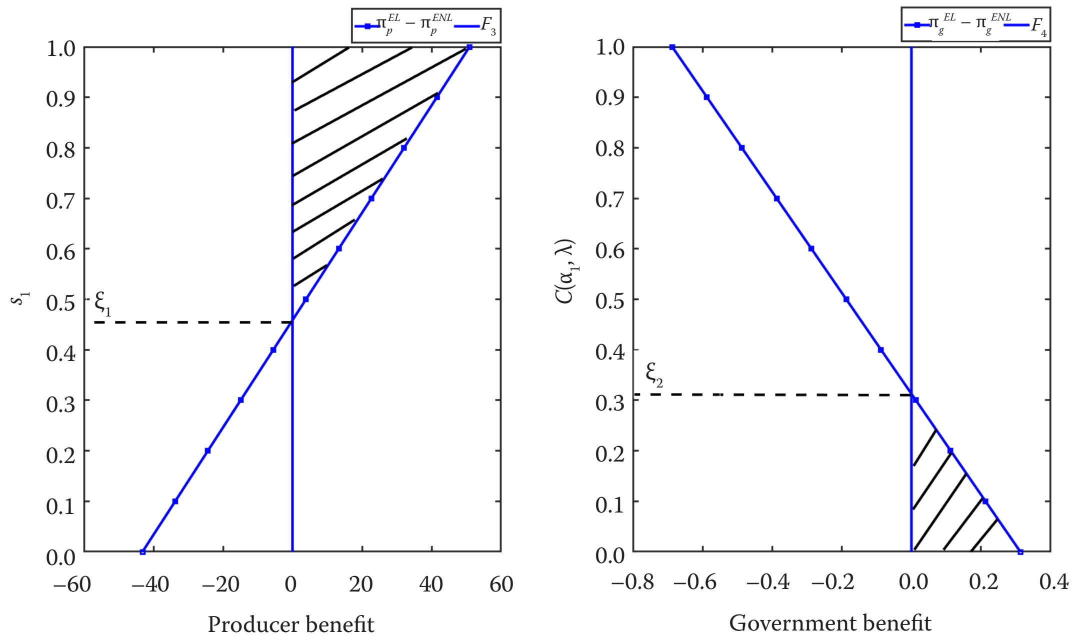

Figure 8. Subsidy conditions and investment conditions for producer

s_1 – :reduction loss subsidy coefficient for the producer; C – costs of agricultural pollution emission reduction technology; α_2 – quantity attenuation factor of grain in the retailer; ξ – equilibrium solution; π – benefit; F – zero mark
Source: Author's own elaboration

expressions for APE and demand may be similar. In addition, the producer's benefit also increased, which is the same as the results of Chen et al. (2017). When the EIS coefficient and APE reduction cost reached

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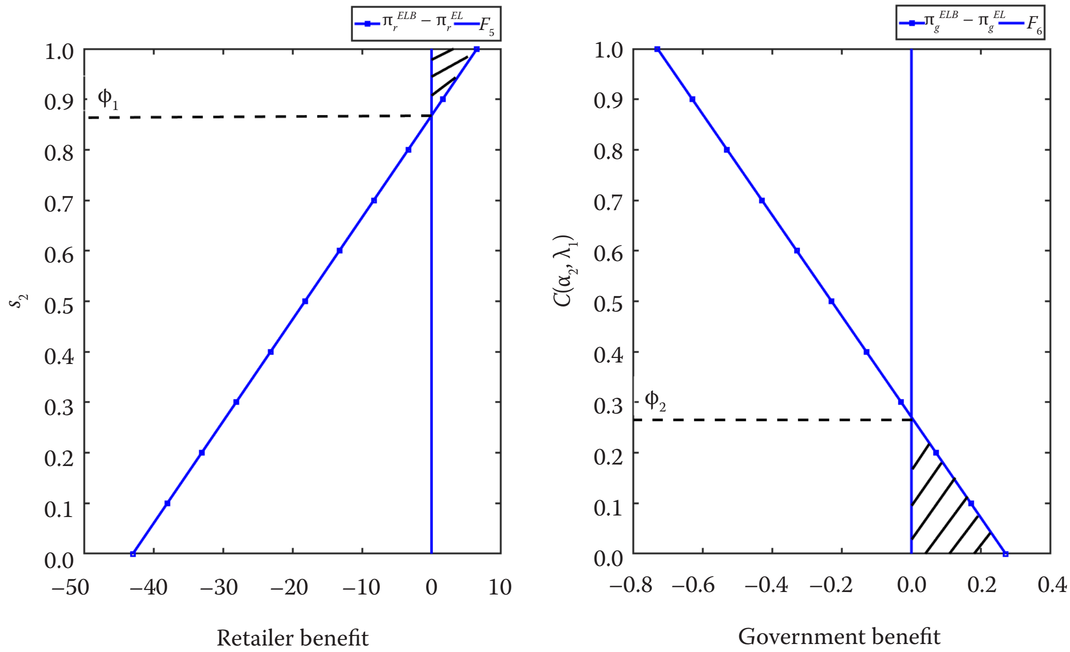

Figure 9. Subsidy conditions and investment conditions for retailer

s_2 – eduction loss subsidy coefficient for the retailer; C – costs of agricultural pollution emission reduction technology; α_2 – quantity attenuation factor of grain in the retailer; ϕ – equilibrium solution; π – benefit; F – zero mark

Source: Author's own elaboration

a certain range, the producer's emission reduction behaviour and the government subsidies helped supply chain members to gain high benefits without adopting innovation. In other words, it is feasible for the government to achieve the goal of environmental protection by subsidising the producer's APE reduction investment, and the result of this study is similar to that of Zhang et al. (2021).

Robustness analysis. Because of global warming, it is particularly important to accomplish the goal of improving air quality. China had formulated a series of beneficial agricultural policies to subsidise the costs of agricultural pollution control (see Appendix D in the ESM). In the ENL, EL and ELB models, we discussed only the case in which the government provides variable subsidies, but, in practice, the government can adopt a mixed subsidy model. For example, subsidies for agricultural film recycling are a variable subsidy model. To support green technology extension services, the government offered fixed and variable subsidy models (Ricker-Gilbert and Jones 2015; Chatterjee 2018). Therefore, we will make the extension models FENL, FEL and FELB. Specific changes are as follows: c_1 indicates the fixed subsidies of the government for APE cost reduction, c_2 indicates the fixed subsidies of the government for producer PHLG cost reduction and c_3 indicates the government fixed subsidy for retailer PHLG cost reduction. The analysis process is shown in Appendix E in the ESM. The results show that when the government provides only the fixed subsidies, these fixed subsidies have no effects on the equilibrium prices in the extended models, but they have an effect on the revenues of supply chain members, which is similar to the results in the variable subsidy model. If the government provides the mixed subsidies, the effect trends of the subsidy coefficients on the equilibrium prices and revenues remain unchanged in the three models, which indicates that the robustness of our constructed model is good.

Investigators in other studies considered the influence of only one factor and did not take into account the influence of APE and PHLG. In addition, the two factors may affect each other, and other investigators did not discuss whether their results would be affected by the combination of factors. Agricultural pollution limits agricultural production as well as environmental sustainability. To alleviate this dilemma, some scholars had obtained important results regarding subsidy policies for the reduction loss and emission investments in agricultural supply chains (Chen et al. 2017; Zhang et al. 2021). In this study, we integrated APE and PHLG to explore the government subsidy strate-

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gies and investment rules of supply chain members to achieve the purpose of encouraging supply chain members to reduce PHLG while achieving APE reduction. In addition, we defined the model based on the study by Zhang et al. (2021) and proposed four subsidy models to analyse comprehensively the effect of APE and PHLG on supply chain members and find the best strategy, which we also verified.

CONCLUSION

Conclusion and policy recommendation. In this study, we proposed the concept and function expressions of APE and PHLG reduction efforts, modified the demand function by considering the dual context of APE and PHLG reduction, proposed and analysed four investment subsidy models according to the actual situation and compared the benefits among the models. We found that no matter which subsidy method was used, it was not a win-win situation for the government to subsidise. On the contrary, it was necessary to subsidise other supply chain members that were within a certain range to achieve a win-win situation.

i) The equilibrium prices and benefits of supply chain members were negatively correlated with the producer's degree of effort towards using APE reduction technology, regardless of whether those supply chain members invested in PHLG technology. We found that the government subsidies for APE technology caused negative revenue growth for supply chain members. We believe that at the inception of implementing APE reduction technologies, a substantial investment in human resources, financial capital and material assets is essential to rehabilitate and enhance the degraded farmland ecosystems, given the heightened degree of ecological damage.

ii) When the government subsidises APE and PHLG technology for other supply chain members, the government should stop subsidising the retailer's input in loss reduction technology to ensure that the government's own revenue is not damaged. In the Material and methods chapter, we showed that after subsidy, the government cannot balance its benefits among supply chain members. Thus, we suggest that the government stop subsidising retailers' PHLG technology inputs.

iii) The government's revenue is constrained by the strength of its subsidies to other supply chain members. In a comparison of all models, for the government, increasing the subsidy amount for the reduction loss and emission inputs does not necessarily lead to an increase in government revenue because there is a threshold value for the amount of the government's subsidy for reduction loss and emission technology. The government's revenue increases when the amount of input for supply chain members' technology is less than the threshold; conversely, when the amount of input is higher than the threshold, the government's revenue will decrease.

iv) When the government provides reduction loss technology subsidies to others, the government's revenue is not always positively correlated with the level of effort of the supply chain members. In the ELB model, the government's revenue was negatively related to the PHLG reduction subsidy coefficient. However, in the EL model, the government's revenue was positively related to the PHLG reduction subsidy coefficient.

On the basis of these study conclusions, we propose the following pragmatic policy directions. Not all technologies will develop in a good direction, and there may be negative effects. The government should use technology rationally and analyse specific problems on a case-by-case basis. The government should rationally subsidise supply chain members' technological input under the premise of ensuring its own revenue. The need for the government to strengthen its APE and PHLG reduction efforts is key. The strategies mentioned above will help ease APE and PHLG.

There are some limitations in this article. Optimal conditions and implementation plan for the government's subsidies are lacking. The mixed subsidy model also needs to be considered. These will be an important direction of our future work.

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