Adoption of Agricultural Technology: Yield Prediction, Cost Reduction, and (Unintended) Welfare Implications

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Abstract

Problem definition: Agricultural technologies (agtech) have become increasingly prevalent, helping farmers not only reduce production costs during the growing season but also guide pre-season crop choices by providing predictions of uncertain crop yields. Although these technologies are intended to benefit farmers, their implications for total welfare remain largely unexplored, as farmers make adoption decisions individually and their profits are determined by market competition. **Methodology/results:** We analyze a game-theoretic model where a mass of heterogeneous farmers, differing in production costs, make pre-season decisions regarding agtech adoption and crop selection between two crops subject to random yields. Agtech is available to adopt at an upfront cost, which offers pre-season yield predictions and in-season cost reduction benefits. By characterizing farmers' technology adoption and crop choices, we show that the total welfare may reduce as the yield prediction becomes more accurate or the adoption cost is lower. This unintended consequence is more likely for crops with lower market potential. The adverse impact of yield prediction can be mitigated or exacerbated through enhanced cost reduction benefits. Additionally, we analyze several model extensions; in particular, we find that providing updated in-season yield signals that enable farmers to exert yield-improving effort does not necessarily enhance welfare. **Managerial implications:** When promoting yield prediction technologies through financial subsidies or investments to improve prediction accuracy, policymakers should carefully assess their welfare consequences by accounting for the market dynamics of farmer adoption and competition. Improving yield prediction should be coupled with sufficiently strong cost-reduction benefits. Moreover, policymakers should account for the heterogeneous impacts across farmers with different levels of crop specialization when addressing income inequality.

Key words: agricultural technology, yield prediction, farmer welfare, supply uncertainty.

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1 Introduction

Agriculture is a vital industry contributing to economic development. Most of the world's agricultural land is managed by smallholder farmers. For example, approximately 85% of India's agriculture sector consists of smallholder farmers. In the United States (US), small family farms account for 89% of farmland (Whitt et al., 2023). To enhance the welfare of these farmers, particularly by mitigating increasingly high production costs, agricultural technology (agtech) has been widely introduced and extensively developed in recent years (Tang et al., 2015; Getahun et al., 2024). These technologies enable farmers to apply inputs such as fertilizer and water with high precision, effectively reducing production expenses and improving operational efficiency.[1] For example, evidence has shown that innovative agtech can reduce the farming costs of corn, soybean, and wheat by 26%, 31%, and 31%, respectively (ARK Invest, 2023).

Beyond reducing production costs and improving operational efficiency during growing seasons, emerging artificial intelligence (AI) and data analytics techniques have become available that may fundamentally transform how farmers manage uncertainty in the planning phase prior to the growing season. With limited land and resources, smallholder farmers are especially vulnerable to crop yield uncertainty caused by varying weather and soil conditions.[2] Besides helping farmers control growing costs, state-of-the-art agricultural intelligence systems have been equipped with AI algorithms to make crop yield predictions based on a wide range of features such as weather patterns, soil characteristics, and historical crop performance, thereby "assisting [farmers] in making informed decisions about crop selection to optimize yields" (Shams et al., 2024, p5695). These innovations promise to empower smallholders to make more informed crop selection decisions, thus enabling them to avoid low-yield outcomes and potentially increase income. The aforementioned agtech innovations have been rapidly gaining traction, receiving policy support, and witnessing growing adoption in both developed and developing markets.[3]

Although the OM literature has examined the welfare effects of policies that reduce production costs and disseminate demand information (Tang et al., 2015; Liao et al., 2019), little is

[1]For example, tractor guidance systems with GPS can result in accuracy within one centimeter when spraying herbicide or applying fertilizer (USDA, 2025). Deere, an agricultural equipment manufacturer, utilizes space-based data to pinpoint variations in soil moisture, nutrient levels, and plant health, enabling farmers to manage irrigation and fertilization in a more cost-efficient manner (Elaine, 2023).

[2]For instance, weather changes can lead to substantial variations in crop yields from year to year (François et al., 2020).

[3]For example, the Canadian government is investing in climate smart and precision technologies "which will help Canada become a world leader in agricultural innovation technologies and help farmers develop new and efficient ways to utilize resources"(Rotz et al., 2019). China is introducing innovative technologies into the agricultural industry, paving the way for China's future development of agriculture industry (Kendall et al., 2017). In India, the agtech market has been rapidly growing due to supportive government initiatives, booming agtech startups, and increasing awareness among farmers. In 2023, the Indian market size for agtech was estimated to be approximately $80 million and is anticipated to reach $140 million by 2028 (Semantic Tech, 2024).

known about how yield prediction technologies affect farmer welfare or how they interact with cost reduction features in agtech systems. Moreover, unlike policy interventions, agtech is often offered as intelligent systems that farmers adopt voluntarily based on their own interests.

To fill these gaps in the literature, we develop a game-theoretic model in which a continuum of farmers choose between two crops, both subject to random yields, and decide whether to adopt agtech before the growing season. Farmers are heterogeneous in production costs across crops, reflecting differences in growing expertise. Farmers who adopt agtech receive a yield prediction to guide their crop choice and may also benefit from reduced production costs during the season. To disentangle these two features, we proceed in a step-by-step manner. We first consider a setting in which agtech provides only yield prediction, allowing us to isolate how improved yield information shapes crop choices and farmer welfare. We then examine an integrated system that combines yield prediction with cost reduction to assess their joint impact.

Our main findings and contributions are as follows. First, to the best of our knowledge, we are the first to analyze farmers' technology adoption and crop selection decisions when the agtech features predictions of uncertain crop yield. By characterizing farmers' equilibrium adoption and crop choices, we show that total farmer welfare can decrease as yield prediction becomes more accurate or as the adoption cost becomes lower, because of intensified competition. This unintended consequence is more likely when crops have lower market potential. As detailed later, our results indicate that yield prediction has substantially different welfare implications from the provision of market demand information documented in the existing literature (Tang et al., 2015; Liao et al., 2019). Hence, when promoting yield prediction technologies through financial subsidies or investments to improve prediction accuracy, policymakers should carefully assess their welfare consequences by accounting for the market dynamics of farmer adoption and competition. Additionally, using the Gini index, we examine how agtech affects farmers differently depending on their level of specialization and, hence, income inequality. In some cases, improving welfare and reducing income inequality through agtech can be conflicting objectives.

When yield prediction is offered along with the cost reduction feature, we find that depending on the adoption cost and individual growing expertise, some farmers may adopt agtech only for the cost reduction benefit while not following the yield prediction to choose crops. We show that a stronger cost reduction feature can also reduce welfare. Together with a comprehensive numerical study, our results provide policy implications on how to configure technology to enhance farmer welfare more effectively. In particular, improving both features simultaneously may reduce welfare, and higher prediction accuracy improves welfare only when market potential is sufficiently high or when the cost reduction feature is strong enough.

Finally, we extend the model along several dimensions. In particular, we find that providing in-season yield monitoring that enables farmers to exert yield-improving effort during the growing season does not necessarily enhance welfare. We also relax key assumptions by considering more than crops, false positive prediction errors, and asymmetric market potentials. Our main findings are robust across all these model extensions.

2 Literature Review

Our work is related to the growing operations management (OM) literature on farmer welfare in agricultural industries. Existing studies have explored various approaches to improving farmer welfare, such as minimum support price (Guda et al., 2021; Chintapalli and Tang, 2021; Kouvelis et al., 2025), commercial contracts (Ayvaz-Çavdaroğlu et al., 2021; Chen and Chen, 2021), and insurance (Hu et al., 2019; Chen et al., 2024). See Gupta et al. (2023) for a comprehensive review of this literature.

Our paper examines an important feature of agtech, providing farmers with predictions of crop yield. Thus, our work is related to the stream of literature on information provision in agricultural industries. However, to the best of our knowledge, all the existing papers are focused on the provision of market demand information, rather than yield information. Chen et al. (2015) build a game model to study whether market demand information can increase farmers' income. They analyze the impact of private and public signals on farmers' welfare, and find that free public signals cannot always improve farmer welfare. Liao and Chen (2017) develop a framework that accommodates a highly asymmetric information structure that allows each farmer to observe different market information before making their production decisions. Zhou et al. (2021) consider the impact of the government's market information disclosure policy on alleviating farmers' poverty when farmers compete on production quantities of a single crop. Different from the above papers, we consider agtech that provides crop yield information (alongside cost reduction benefits). Moreover, unlike prior work that focuses on information provision interventions where a government or NGO offers information to targeted farmers, we consider a setting in which farmers self-select into agtech adoption.

In the stream of literature on demand information provision,[4] more relevant to our work are Tang et al. (2015) and Liao et al. (2019). Tang et al. (2015) consider the provision of market information along with agricultural advice that helps farmers reduce production costs and improve product quality. In their model, two farmers compete on production quantities of

[4]Additionally, and more distantly related to our work, there are papers that study the impact of market information on various different issues, such as a farming cooperative's quality certification decisions (Bian et al., 2022) and the incentives of peer-to-peer information sharing (Chen et al., 2015; Xiao et al., 2020).

a single crop, and the crop has uncertain market potential. The two farmers can decide whether to use the market information and agricultural advice. Liao et al. (2019) examine a model in which multiple farmers choose between two types of crops to grow based on the provided market demand information, and they focus on how a central planner should disseminate this information across farmers. Our model is substantially different from theirs in the following primary aspects: (i) We focus on two features of agtech, the provision of crop yield prediction (instead of demand information) along with a benefit of cost reduction; and (ii) in our model, farmers decide whether to adopt agtech and hence receive yield information to maximize their expected payoffs, whereas in Liao et al. (2019), the information provision policy is controlled by a central planner. As will be detailed in Section 4.2, our results indicate that the provision of yield information has substantially different implications on farmer welfare compared to that of demand information.

Our model features random production yield, thus related to the large body of literature on managing yield uncertainty (see Wang et al., 2010; Tang and Kouvelis, 2011; Kouvelis et al., 2021; Dong et al., 2022, and references therein). Studies have explored yield information sharing across vertical supply chain members in manufacturing industries (Choi et al., 2008; Lu, 2024). However, to our knowledge, no existing literature has investigated the impact of yield information provision to small farmers in agricultural industries. A few papers examine the implications of crop yield improvement, rather than providing farmers with yield information (to help them choose between different crops). Li et al. (2024) and Zhang and Swaminathan (2020) consider various ways to improve farmers' yield in an uncertain market such as subsidies and planting schedules. Akkaya et al. (2021) consider agricultural innovation to improve crop yield, and focus on the impact of different intervention strategies on the adoption of agricultural innovations.

From the modeling perspective, the cost reduction feature of agtech captured in our model is loosely related to existing papers on the effect of farmer subsidies, as subsidies can be regarded as a way to reduce farmers' production costs. For example, Alizamir et al. (2019), Guo et al. (2022), Fan et al. (2024), and Tang et al. (2024) have explored various types of subsidies, such as production cost subsidies, harvest subsidies, price subsidies, green material subsidies, etc. Recently, Lu et al. (2024) analyze the use of index-based subsidies that protect smallholder farmers from low yield, where the index is determined based on yield prediction. Vastly different from these papers, our work is motivated by emerging technologies that typically offer both cost reduction and yield prediction features. Our analysis highlights the nontrivial interplay between these two features and their implications for farmers' crop choices and welfare.

3 The Model

Heterogeneous Farmers. We consider a set of infinitesimal farmers in a geographic region, each endowed with a production capacity of one unit and choosing between two crops, indexed by $i = 1, 2$, to grow. The total number of farmers is normalized to one. Following the literature (e.g., Liao et al., 2019), we assume that farmers have distinct expertise in growing these two crops, thus incurring heterogeneous production costs, captured by a parameter θ that is uniformly distributed along a Hotelling line $[-1/2, 1/2]$. The two crops are located at the opposite ends of the line, i.e., crop 1 is located at -1/2 and crop 2 is located at 1/2, and each farmer chooses one of the crops to grow (see Figure 1). For a farmer located at some θ, the production costs of crops 1 and 2 are given by $c_1(\theta) = t(1/2 + \theta) + C$ and $c_2(\theta) = t(1/2 - \theta) + C$, respectively. The first terms associated with the location parameter θ capture farmers' heterogeneous efficiency in growing different crops; for example, farmers with θ closer to point 1/2 on the Hotelling line are more specialized in growing crop 2. The coefficient t captures the degree of heterogeneity across farmers. A larger t implies that it is more costly for a farmer specialized in one crop to switch to the other crop. The second term C represents a fixed baseline production cost that incorporates common expenditures, independent of individual growing expertise, such as land leasing, seed procurement, and fixed capital investments (e.g., equipment and infrastructure). Note that heterogeneity in production costs is consistent with empirical evidence showing that production efficiency differs significantly across individual farmers.[5]

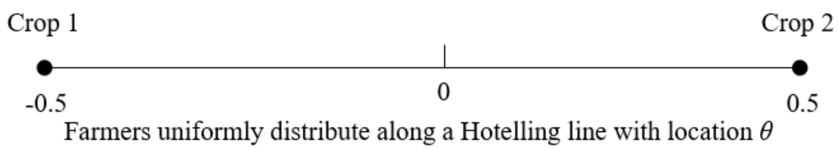


Figure 1: The location of two crops

Uncertain Yield. As is common in agricultural industries, each farmer has an uncertain yield. If a farmer chooses to grow crop i, the actual output of the farmer is z_i, which is a random variable. It represents the yield uncertainty associated with each crop i, which is attributed to the common factors to all farmers in the region, such as precipitation, soil and other environmental conditions. For example, the yield of crop 1 can be more sensitive to high precipitation than that of crop 2. There are two possible states associated with z_i, denoted by $\delta_i = H$ or L. The value of z_i under state δ_i is μ_H or μ_L, where $\mu_L < \mu_H$. Thus, we can interpret H and L as the

[5]Empirical evidence indicates that the expense ratio, defined as operational expenses divided by gross revenue, ranges from 52% to 81% across farmers, suggesting a substantial efficiency gap: For the same level of revenue, farmers with lower expertise may incur nearly 30% higher total costs than more experienced peers (Bradley, 2024).

good and bad states for each crop, respectively. For ease of notation, we assume that $\mu_H = 1$ and $\mu_L = \mu$, where $0 \leq \mu < 1$.

For notational brevity, we assume that states H and L occur with equal probabilities for each crop, i.e., each crop will be in state $H(L)$ with probability $1/2$. We allow the region-level yield factors z_1 and z_2 to be correlated. The joint distribution is determined by the probabilities $p_{\delta_1\delta_2},\ \delta_i \in H, L, i = 1, 2$ such that

$$p_{HH} + p_{HL} + p_{LH} + p_{LL} = 1, \tag{1}$$

$$p_{HH} + p_{HL} = p_{HH} + p_{LH} = 1/2. \tag{2}$$

Equation (1) ensures that the sum of the probabilities of all events is 1. Equation (2) captures the crop correlation while keeping the marginal probability of the high state as $1/2$. We can obtain the correlation coefficient for two crops as $\rho = \frac{p_{HH}-1/4}{1/4}$. Notice that $\partial\rho/\partial p_{HH} > 0$; hence, as in Babich et al. (2007), we can use $p_{HH} \in [0, 1/2]$ to measure the degree of correlation. The correlation of the two crops increases with p_{HH}. Specifically, when $p_{HH} = 0$, we have $p_{HL} = p_{LH} = 1/2$ and so the yields of two crops are perfectly negatively correlated; when $p_{HH} = 1/2$, $p_{HL} = p_{LH} = 0$ and so the yields are perfectly positively correlated. For example, rice cultivation generally requires a warm environment, whereas wheat is a relatively cold-resistant crop that can grow in cooler climates. Some crops, such as tea and blueberries, prefer acidic soil environments, while others, like soybeans and sugar beets, are adapted to alkaline soil environments. In practice, alternative crops cultivated within the same region often share similar preferences to local environmental factors, such as precipitation and temperature. Consequently, their yields typically exhibit positive correlations. Motivated by this empirical observation, our subsequent analysis and numerical experiments will primarily focus on the positive correlation regime, where $p_{HH} \in [1/4, 1/2]$. Nevertheless, it is worth noting that our analytical results remain robust and hold for the entire feasible range $p_{HH} \in [0, 1/2]$.

Farmer Profit. For expositional brevity, we assume that the two crops will be sold in two independent markets with identical market potential a. The case with asymmetric market potentials will be discussed in §6.4. In line with the literature (e.g., Tang et al., 2015; Liao et al., 2019), the market price of each crop i (where $i = 1, 2$) is determined by an inverse linear demand function, $a - Q_i$, where a is the market potential and Q_i denotes the total supply of crop i in the market. Let q_i denote the proportion of farmers who choose to grow crop i. Because farmers are infinitesimal, the total quantity of crop i is given by $Q_i = q_i z_i$.[6] Therefore,

[6] In fact, we can allow the yield of a farmer θ growing crop i to be subject to an idiosyncratic shock $\epsilon_{i\theta}$, in addition to and independent of z_i. The yield from a farmer can be represented by $y_{i\theta} = z_i + \epsilon_{i\theta}$. We assume

conditional on z_i, a farmer located at θ will earn the following profit if choosing crop i:

$$\pi_i = z_i(a - q_i z_i) - c_i(\theta). \tag{3}$$

In our base model setting, yield and production cost are independent. This simplification allows us to capture each farmer's efficiency through production cost: Given the same level of yield uncertainty, a more efficient farmer incurs a lower cost. In Section 6.1, we allow farmers to exert additional effort to improve yield, thereby reflecting the realistic feature that higher yields are often associated with higher costs.

Agriculture Technology. In the base model, we consider the yield prediction feature of agtech first. Farmers incur a cost $K > 0$ if adopting the technology. As indicated by GAO (2024), it often requires a considerable upfront cost for farmers to acquire the related tools.

In the pre-season, agtech can predict the potential yield of optional crops, farmers receiving the information can choose a high-yield crop to grow. We model the yield prediction with a two-dimensional binary signal: $\mathbf{s} = (s_1, s_2)$, where $s_i \in H, L$ for $i = 1, 2$. Signal s_i is a prediction of crop i's state. We allow the signal to be imperfect in the following sense. Given that the true state of crop i is H, $s_i = H$ with probability one. However, given that the true state of crop i is L, the technology will successfully forecast the bad state by an "L" signal, i.e., $s_i = L$, with probability β. We will refer to β as the prediction accuracy of agtech. This assumption, though made for tractability, is in line with the practice that yield prediction technologies usually provide early warnings for undesired environmental conditions (Spratt, 2023). Based on the above signal structure, we can derive the probabilities of the four possible signal realizations, i.e., $(s_1, s_2) = (H, H)$, (H, L), (L, H), and (L, L), as follows. $\Pr(s_1 = H, s_2 = H) = p_{HH} + p_{HL}(1-\beta) + p_{LH}(1-\beta) + p_{LL}(1-\beta)^2$, $\Pr(s_1 = H, s_2 = L) = \Pr(s_1 = L, s_2 = H) = \beta p_{HL} + (1-\beta)\beta p_{LL}$, $\Pr(s_1 = L, s_2 = L) = \beta^2 p_{LL}$. Farmers know the prior distribution specified in Equations (1) and (2), and can therefore form a posterior belief after observing a signal (s_1, s_2). Denote by $\eta_i(s_1, s_2)$ the posterior probability that crop i will be in state H conditioning on a farmer observing signal (s_1, s_2), i.e., $\eta_i(s_1, s_2) = \Pr(\delta_i = H | s_1, s_2) = \frac{\Pr(\delta_i = H)\Pr(s_1, s_2 | \delta_i = H)}{\Pr(s_1, s_2)}$. Invoking Equations (1) and (2) and Bayes' rule, we have $\eta_1(H, H) = \eta_2(H, H) = \frac{\beta p_{HH} + \frac{1}{2}(1-\beta)}{1 - \beta + p_{HH}\beta^2}$, $\eta_1(H, L) = \eta_2(L, H) = \frac{1 - 2p_{HH}}{1 - 2\beta p_{HH}}$, and $\eta_1(L, H) = \eta_2(H, L) = \eta_1(L, L) = \eta_2(L, L) = 0$. To see how the crop correlation influences these posterior probabilities, suppose that the yields of the two crops are perfectly positively correlated, i.e., $p_{HH} = p_{LL} = 1/2$. Conditional on a signal (H, L), the posterior probability of crop 1 being in state H is reduced to 0, i.e., $\eta_1(H, L) = 0$. This is because, under

that $\epsilon_{i\theta}$ is independent and identically distributed (i.i.d.) across farmers with mean zero. Because farmers are infinitesimal, the idiosyncratic shocks $\epsilon_{i\theta}$ cancel out as we calculate the total output Q_i; therefore, they have no effect on our results.

our information structure, $s_2 = L$ confirms that crop 2 is in a bad state, whereas $s_1 = H$ does not necessarily imply a good state for crop 1. Yet, knowing the perfectly positive correlation between crops, farmers will infer that crop 1 must also be in state L. One may interpret the signal as a growing recommendation provided by agtech. However, individual farmers may or may not follow the recommendation when they receive the signal, depending on their expertise captured by θ.

Farmers' Agtech Adoption and Crop Choices. Farmers decide whether to adopt agtech and which crop to grow to maximize their expected profits. Without agtech, farmers will evaluate the expected profit from growing each crop, i.e., $\mathbb{E}[\pi_1]$ and $\mathbb{E}[\pi_2]$, based on the prior distribution given in Equations (1) and (2). A farmer at location θ will choose crop 1 if and only $\mathbb{E}[\pi_1] \geq \mathbb{E}[\pi_2]$. Let $U_N = \max_{i=1,2} \mathbb{E}[\pi_i]$ represent the (maximum) expected profit if a farmer does not adopt the technology. With agtech, farmers will be able to decide which crop to grow based on the signal (s_1, s_2). Conditional on any realized signal (s_1, s_2), a farmer at location θ will obtain the following expected profit

$$\mathbb{E}(\pi_i|s_1, s_2) = a\mathbb{E}(z_i|s_1, s_2) - q_i(s_1, s_2)\mathbb{E}(z_i^2|s_1, s_2) - c_i(\theta) - K \tag{4}$$

if growing crop i, where $q_i(s_1, s_2)$ denotes the proportion of farmers who choose crop i under signal (s_1, s_2). Now the crop choice is signal dependent. Consequently, with the technology, farmers will obtain an expected profit

$$U_A = \sum_{s_1, s_2 \in \{H, L\}} \Pr(s_1, s_2) \max_{i \in \{1,2\}} \mathbb{E}(\pi_i|s_1, s_2). \tag{5}$$

A farmer will adopt the technology if and only if $U_A \geq U_N$.

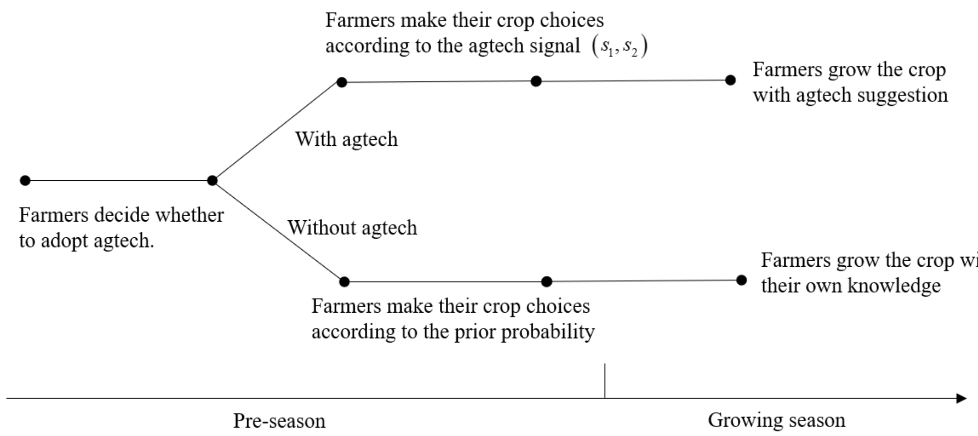


Figure 2: Sequence of events

The sequence of events is summarized as follows; see also Figure 2. (1) First, each farmer decides whether to adopt agtech at a cost K by comparing U_A and U_N. (2) Then, farmers with agtech receive a realized signal (s_1, s_2), based on which they make their crop choice; farmers without agtech select the crop based on the prior probability distribution of (z_1, z_2). (3) Finally, actual yields are realized and market prices determined; farmers receive their profits accordingly.

4 Implications of Yield Prediction

In this section, we will first characterize the farmers' optimal crop choices and examine their agtech adoption decisions. After characterizing the market equilibrium, we will discuss the implications of the technology on farmer welfare and income inequality.

4.1 Farmer Decisions

In the following proposition, we analyze the farmers' technology adoption decisions and crop choices in equilibrium. Without agtech, farmers will select a crop based on the prior distribution where two crops have equal probabilities of being in a good state. It is easy to verify that they will choose the crop closer to their location θ; hereafter, we refer to this crop as their "default" crop. Note that the adoption of agtech will influence farmers' crop choices only when the realized signal favors one crop over another, i.e., $\mathbf{s} = (H, L)$ or (L, H).[7] Hereafter, we will say a crop is "recommended" by agtech if the realized signal is H for the crop but is L for the other crop. When agtech is introduced, adopters' decisions are characterized by Proposition 1.

Proposition 1. *Farmers' agtech adoption decisions and crop choices in equilibrium are characterized below.*

(i) *There exists a threshold* $\bar{\theta} = \frac{2a\beta\mu - 2a\beta - 2\beta(\mu-1)(2a-\mu-1)p_{HH} - \beta\mu^2 + \beta + 4K}{4\beta p_{HH}((2\beta-1)\mu^2 + 2\beta t + 1) - 2(\beta(\mu^2+1) + 2t((\beta-1)+1))}$ *such that farmers located within* $[-\bar{\theta}, \bar{\theta}]$ *will use the technology, and all of them will choose crops based on the signal (follow the signal), i.e., growing the recommended crop when the signal is* (H, L) *or* (L, H)*. When the signal is* (H, H) *or* (L, L)*, farmers will choose their default crop.*

(ii) *For any given signal, the number of farmers growing crop* i *under signal* (s_1, s_2) *is given by* $q_1(H, H) = q_2(H, H) = q_1(L, L) = q_2(L, L) = \frac{1}{2}$, $q_1(H, L) = q_2(L, H) = \frac{1}{2} + \bar{\theta}$, *and*

[7] With the technology, the number of farmers choosing each crop and hence the indifference point will be signal-dependent. Given $\mathbf{s} = (L, L)$ or (H, H), in farmers' posterior belief, the two crops still have the same yield risk (although the probability of each state is updated), and so the indifference point remains as 0. However, if signal $\mathbf{s} = (H, L)$ or (L, H), the signal implies that one crop is more likely in a good state than the other. Specifically, a signal (H, L) indicates that crop 1 will more likely have a high yield, thus more farmers will opt for crop 1. Similarly, a signal (L, H) will make more farmers choose crop 2.

$q_2(H, L) = q_1(L, H) = \frac{1}{2} - \bar{\theta}$. The number of adopters as well as the total supply of recommended crops are increasing in prediction accuracy β.

The proofs for all our results can be found in Appendix A2. In general, farmers located within a middle range of the Hotelling line tend to adopt agtech, whereas those near the two ends do not. This is because the farmers in the middle incur high and similar production costs for both crops, thus easily switching crop and benefiting more from the signal than those near the ends. In contrast, farmers near the ends are more specialized in growing one crop than another and thus tend to retain their default crops, making them unresponsive to the signal.

In addition, a larger $\bar{\theta}$ signifies a greater number of adopters. Proposition 1(ii) examines the effect of yield prediction accuracy β on the number of adopters and the quantities of recommended crops supplied to the market. This aligns with intuition: As the signal becomes more accurate, a larger number of farmers are incentivized to adopt the technology. Although farmers have a cost advantage when growing their default crop, following the high-accuracy signal's recommendation significantly enhances their expected yields, thereby increasing the total supply of the recommended crop.

4.2 Implications on Farmer Welfare

In this subsection, we examine the impact of agtech on the total farmer welfare. By the uniform distribution of θ and Proposition 1, when agtech is available for adoption, the farmer welfare, denoted by W^A, can be expressed as

$$W^A = 2\left[\int_{-0.5}^{-\bar{\theta}} U_n(\theta)d\theta + \int_{-\bar{\theta}}^{0} U_{ado}(\theta)d\theta\right]$$

where $U_n(\theta)$ and $U_{ado}(\theta)$ are the expected profits of each nonadopter and adopter, respectively, as functions of θ. The closed-form expressions of these functions are presented in Appendix A2.

Counter to intuition, we show that higher yield prediction accuracy β may hurt farmer welfare, while a higher adoption cost K may enhance it.

Proposition 2. *With all else fixed, (i) the farmer welfare W^A can be decreasing in the yield prediction accuracy β when the market potential a is lower than a threshold $\bar{a}$; and (ii) the farmer welfare W^A can be increasing in the adoption cost K when the market potential a is lower than a threshold $\bar{a}'$.*

Proposition 2 establishes that enhanced yield predictions can lead to an unintended consequence on the farmer welfare when the crops have low market potential. Although more effective prediction technology enables each individual adopter to make more informed crop selection, it will induce more adopters in the market and indirectly affect the total farmer welfare W^A. Given sufficiently low market potential, this indirect effect can be negative due to intensified competition, and may serve as a dominant factor leading to a reduction in total welfare. Similarly, when market potential is low, although the technology adoption cost K reduces the number of farmers adopting the technology, it may have a positive impact on welfare by mitigating competition in the market for the recommended crop. In practice, the cost K could be reduced as the government subsidizes agtech adoption. Our results suggest that policymakers should carefully assess market conditions and potential welfare impacts when designing subsidies for agtech services with yield prediction features.

Does the introduction of predictive agtech always enhance farmer welfare, compared to a scenario where agtech is not available? Let W^N denote the farmer welfare when agtech is unavailable. Note that W^N is equal to W^A when the adoption cost K is prohibitively high such that the number of adopters is zero (i.e., $\bar{\theta} = 0$). Our earlier results seem to suggest that stronger features hurt farmers when the market potential is low. In fact, this condition is sufficient but *not* necessary. In Proposition 3, we establish that regardless of how large the market potential a is, one can always find a set of prediction accuracy β such that the farmer welfare decreases as the technology is introduced.

Proposition 3. *For any (arbitrarily large) market potential a, there always exists a nonempty set of β such that the introduction of agtech hurts the farmer welfare, i.e., $W^A < W^N$.*

Our result can be explained by the individual-level profit of each farmer. As shown in Figure 3, the solid line captures the individual profit of each farmer located at θ when agtech is introduced, i.e., U_A and U_N capture the profits of adopters and non-adopters. The dotted line captures those when agtech is not available. Farmers in the very middle part of the Hotelling line (i.e., in $[-\theta', \theta']$) incur similarly high costs for both crops. Thus, as agtech becomes available, these farmers will have the greatest incentive to adopt it and follow the signal. Although they benefit the most from agtech, their crop choices, influenced by the signal, can increase the supply of the recommended crop, thus decreasing its market price and negatively impacting other farmers' profits. Proposition 3 establishes that even when the number of adopters in the middle is arbitrarily small, the introduction of agtech, despite benefiting this small group of adopters, will hurt the other farmers and reduce the overall welfare.[8] Furthermore, it can be observed that for farmers located in $[-\bar{\theta}, -\theta') \cup (\theta', \bar{\theta}]$, although their profit after adopting agtech

[8]Technically, Proposition 3 is proved by, for any given a, constructing a range of parameter β such that W^A decreases as $\bar{\theta}$ increases from 0 (in which case $W^A = W^N$) to a small positive value.

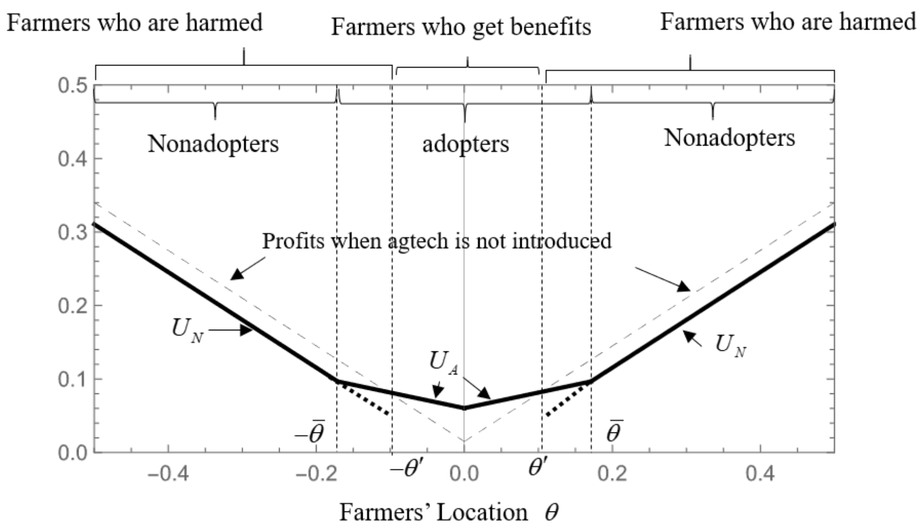


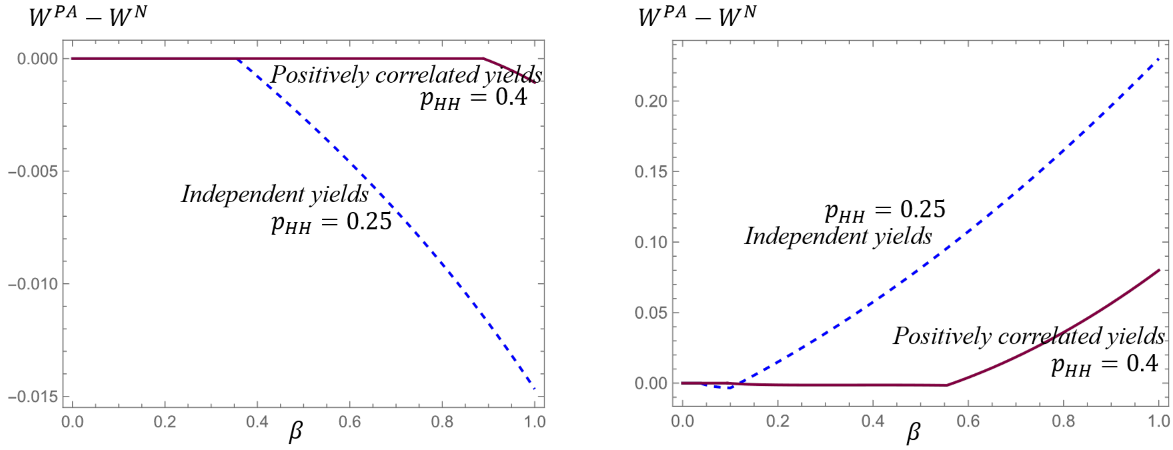
Figure 3: Impact of yield prediction on individual profits: (i) farmers in $[-\theta', \theta']$ benefit from the technology; (ii) farmers in $[-\bar{\theta}, -\theta') \cup (\theta', \bar{\theta}]$ adopt the technology with limit benefits but are hurt by the adoption cost; (iii) farmers in $[-1/2, -\bar{\theta}] \cup [\bar{\theta}, 1/2]$ do not adopt the technology and are hurt by intensified competition.

is higher than it would be without adoption, it remains lower than the profit earned when the technology was unavailable. This indicates that such farmers are trapped in a dilemma: They are compelled to adopt agtech to mitigate losses, yet they are ultimately worse off than in the absence of agtech.

It is noteworthy that providing yield predictions is somewhat related to the extant literature on the provision of demand information among farmers (Tang et al., 2015; Liao et al., 2019). However, our Proposition 2 indicates that providing more accurate yield information can hurt farmer welfare, whereas the extant literature shows that providing demand information always improves farmer welfare (e.g., propositions 1 and 2 in Liao et al., 2019).[9] Thus, the provision of yield information has substantially different welfare implications than that of demand information. Under demand information provision in Liao et al. (2019), which also examines heterogeneous farmers choosing between two crops, the market crowding-induced price drop for the predicted high-demand crop is offset by an equal price increase for the alternative crop, leaving the expected profits of non-adopters completely unaffected. In contrast, under our framework, the resulting high yield further amplifies the market crowding effect, causing the price of the high-yield crop to fall much more than the price of the other crop rises, thereby reducing non-adopters' expected profits.[10] Therefore, compared to the extant literature, our

[9]Note that in Liao et al. (2019), providing demand information to too many farmers may reduce total welfare due to intensified competition, but an increase in information accuracy is always welfare-improving.

[10]Another substantial difference between our work and Liao et al. (2019) is that in our model, farmers self-select whether to adopt agtech whereas in Liao et al. (2019) the government controls who receives the demand information. For this reason, in our setting, when a very small group of farmers have access to yield information,



(a) Low market potential $a = 1$ (b) High market potential $a = 3$

Figure 4: The effect of correlation

results suggest that the provision of yield information requires more caution than that of market demand information, because yield uncertainty exacerbates the market crowding effect, harming specialized farmers who retain their default crops.

To complement our analytical results and derive further insights, we present a series of numerical examples. To ground the numerical study in real-world agricultural practices, in all our numerical examples, the model parameters are calibrated to empirical data, primarily drawing from the U.S. Department of Agriculture (USDA) databases and farmdoc daily crop reports. Specifically, we set the baseline parameters as $t = 0.25$, $\mu = 0.5$, $K = 0.02$, and $C = 0.5$ and vary other parameters as needed. A detailed discussion regarding our model calibration is relegated to Appendix A1.

Recall that a larger probability p_{HH} signifies a higher correlation between the yields of two crops, with $p_{HH} = \frac{1}{2}$ (resp. $p_{HH} = 0$) representing perfectly positive (resp. negative) correlation. Intuitively, as the yields become more positively correlated, the role of yield prediction in crop selection will be weakened, and so the effect on welfare, either positive or negative, will be reduced.

Example 1. (Effect of Yield Correlation) As shown in Figure 4(a), when the market potential is low ($a = 1.2$), the prediction accuracy has a negative effect on the welfare, a higher yield correlation alleviates the negative effect. Given $p_{HH} = 0.25$, farmers adopt agtech earlier, but welfare is more likely to fall below the baseline level. Conversely, when $p_{HH} = 0.4$, farmers will

further enhancing the feature to attract more adopters may harm total welfare. In contrast, in Liao et al. (2019), when the number of informed farmers is sufficiently small, expanding the breadth of information provision always improves farmer welfare. Additionally, Tang et al. (2015) consider demand information provision in a single-crop model where two farmers engage in Cournot competition by choosing production quantities. As shown in their corollaries 3, 5, and 6, the provision of demand information always benefits farmers because it helps farmers better adjust their production quantities to ease competition.

only adopt agtech at a higher β, but the decline in welfare is mitigated. As shown in Figure 4(b), when the market potential is high ($a = 5$), an increase in yield correlation attenuates the positive effect of prediction accuracy.

Our observations from Example 1 suggest that farmer welfare is more sensitive to the accuracy of yield prediction when the yield correlation is lower. In such cases, the welfare impact of offering yield predictions should be assessed with greater caution.

4.3 Impact on Income Inequality

Our Hotelling line-based model reflects the reality that specialized farmers (located near the two ends of the Hotelling line) tend to earn a higher income than farmers who do not specialize in either crop (in the middle of the Hotelling line). Our preceding discussion in Section 4.2 has alluded that the introduction of agtech has an impact on income inequality. Farmers with different levels of specialization have different incentives to adopt agtech. Now we analyze the impact of agtech on farmers' income inequality using the *Gini coefficient*, a commonly used metric for income inequality. The Gini index measures the extent to which the distribution of income among individuals within an economy deviates from a perfectly equal distribution, which is defined based on the Lorenz curve (Tang et al., 2024; Giorgi and Gigliarano, 2017). The Lorenz curve plots the proportion of the total income of the population (y-axis) that is cumulatively earned by the bottom x of the population. The Gini coefficient measures the ratio of the area that lies between the line of equality and the Lorenz curve over the total area under the line of equality.[11] Specifically, in our model, the Lorenz curve can be defined as:

$$L(x) = \begin{cases} \frac{2}{W^A} \int_0^{\frac{x}{2}} U_{ado}(\theta) d\theta & \text{for } x \in \left[0, 2\bar{\theta}\right], \\ \frac{2}{W^A} \left(\int_0^{\bar{\theta}} U_{ado}(\theta) d\theta + \int_{\bar{\theta}}^{\frac{x}{2}} U_n(\theta) d\theta \right) & \text{for } x \in [2\bar{\theta}, 1]. \end{cases}$$

Then, the Gini coefficient can be represented by:

$$G = 1 - 2 \int_0^1 L(x) dx \tag{6}$$

A Gini coefficient of 0 indicates complete equality, where all income values are identical, whereas a Gini coefficient of 1 (or 100%) signifies extreme inequality among values, depicting a scenario where one individual possesses all the income, leaving none for everyone else.

Example 2. (Impact on Income Inequality) We plot the Gini coefficient and the total welfare

[11] See more details at `https://databank.worldbank.org/metadataglossary/jobs/series/SI.POV.GINI` accessed September 2, 2024

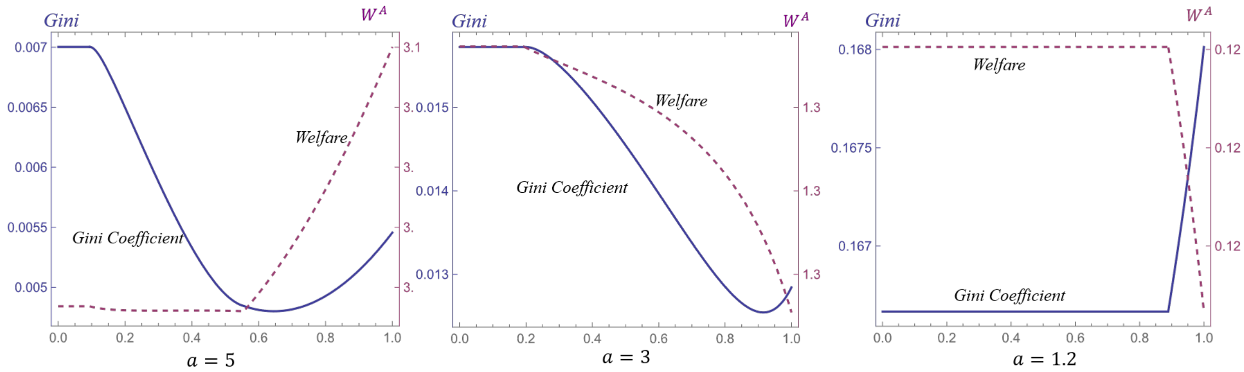


Figure 5: Income inequality implications of agtech (see parameter calibration in Appendix A1)

as functions of yield prediction accuracy β in Figure 5. We have the following observations from panels (a), (b) and (c).

(a) When the market potential is high ($a = 5$), a higher yield prediction can simultaneously enhance the total welfare and reduce income inequality (i.e., result in a lower Gini coefficient) in most cases, as prediction accuracy β increases. As explained earlier, this is because the nonspecialized farmers in the middle of the Hotelling line benefit the most from agtech, whereas their adoption can reduce the profits of specialized farmers through intensified competition in the market of recommended crops, thus easing the income inequality. However, as β further increases, agtech paradoxically exacerbates income inequality by further amplifying the advantage of the non-specialized farmers.

(b) When the market potential is low ($a = 1.2$), a higher β can hurt the total welfare and also exacerbates income inequality. This is because, given a low market potential, a higher β reduces total welfare more prominently than it reduces the absolute difference in farmers' incomes. As a result, the income gap relative to total income increases with β, leading to a rise in the Gini coefficient.

(c) Given the medium market potential $a = 3$, the Gini coefficient decreases in β, implying that an appropriately high β can alleviate income inequality; however, in this example, a higher β always hurts total welfare.

The above observations imply that yield prediction technology can help improve farmer welfare and alleviate income inequality only if crops have sufficient market potential. Although yield prediction reduces the absolute income difference between specialized and nonspecialized farmers, in the case of low market potential, its welfare-reducing effect may outweigh its impact on the absolute income difference, leading to an increase in the Gini coefficient. In some cases, alleviating income inequality and improving welfare can be conflicting objectives when both are pursued through the provision of yield prediction.

5 Implications of Integrated Yield Prediction and Cost Reduction Features

In practice, agtech services are often delivered through an integrated intelligence system or platform that combines multiple technological features (such as the services from John Deere and Bayer). As mentioned earlier, alongside emerging yield prediction technologies, existing agricultural technologies have enabled more precise use of fertilizer, herbicides, water, and energy during the growing season, thereby helping farmers lower their production costs. In this section, we further explore how an integrated agtech service, combining both the yield prediction and cost reduction features, influences the equilibrium outcome and farmer welfare.

We assume that using the integrated service, each farmer's expertise-related production cost will be reduced by a factor $(1-\omega)$, where $0 \leq \omega \leq 1$, regardless of which crop they grow. As such, with the service, a farmer at location θ will incur a cost $c_1^A(\theta) = \omega t(0.5+\theta) + C$ if growing crop 1, and a cost $c_2^A(\theta) = \omega t(0.5-\theta) + C$ if growing crop 2. With this specification, we assume that the agtech service helps reduce expertise-related production costs while leaving the baseline cost C unchanged. This assumption is empirically grounded as it reflects the reality that agtech can effectively lower the expertise-dependent costs by, e.g., guiding less experienced farmers to utilize water and fertilizers more efficiently, but it does not reduce indispensable expenses such as land leases and basic seed procurement. For brevity, we define $\tau = 1-\omega$ as the level of cost reduction achieved, where a larger τ signifies a greater magnitude of cost reduction.

The incorporation of cost reduction adds significant complexity to farmers' joint decisions. Define $\bar{K} = \frac{\tau t}{2}\left[1 - \frac{(2a-1-\mu)(1-\mu)(1-2p_{HH})}{(1+\mu^2+2t(1-\tau))-(2-(2-4\beta)\mu^2+4t\beta(1-\tau))p_{HH}}\right]$. As opposed to the case with only yield prediction feature, depending on whether the adoption cost K is greater or smaller than $\bar{K}$, some farmers may adopt the service only for the cost reduction feature while not leveraging yield predictions.

Proposition 4. *Farmers' agtech service adoption decisions and crop choices in equilibrium are characterized by one of the two cases below.*

(i) If the adoption cost $K \leq \bar{K}$, there exits thresholds $\bar{\theta}^i \geq \hat{\theta} \geq 0$ such that the farmers located within $[-\bar{\theta}^i, \bar{\theta}^i]$ will adopt the service, and only a subset of the adopters, located within $[-\hat{\theta}, \hat{\theta}] \subset [-\bar{\theta}^i, \bar{\theta}^i]$, will choose crops based on the signal. For any given signal, the number

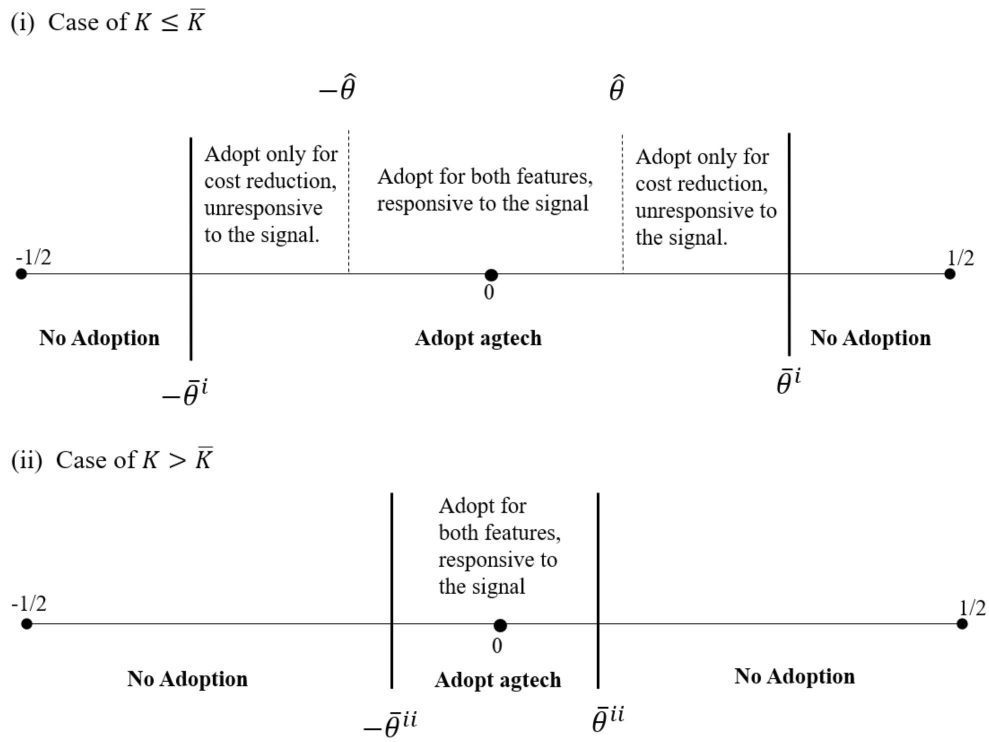


Figure 6: Segments of the farmers

of farmers growing each crop is given by $q_1(H,H) = q_2(H,H) = q_1(L,L) = q_2(L,L) = \frac{1}{2}$*,* $q_1(H,L) = q_2(L,H) = \frac{1}{2} + \hat{\theta}$*, and* $q_2(H,L) = q_1(L,H) = \frac{1}{2} - \hat{\theta}$*.*

(ii) If the adoption cost $K > \bar{K}$*, there exists a threshold* $\bar{\theta}^{ii} \geq 0$ *such that farmers located within* $[-\bar{\theta}^{ii}, \bar{\theta}^{ii}]$ *will use the service, and all of them will choose crops based on the signal, For any given signal, the number of farmers growing each crop is given by* $q_1(H,H) = q_2(H,H) = q_1(L,L) = q_2(L,L)=\frac{1}{2}$*,* $q_1(H,L) = q_2(L,H)=\frac{1}{2} + \bar{\theta}_{ii}$*, and* $q_2(H,L) = q_1(L,H) = \frac{1}{2} - \bar{\theta}_{ii}$*,*

Proposition 4 is illustrated by Figure 6. Notably, when the cost reduction feature is considered, if the adoption cost K is low enough, farmers may adopt the agtech service for different purposes. Farmers within the middle range $[-\hat{\theta}, \hat{\theta}]$ adopt the agtech service and benefit from both the yield prediction and cost reduction features, whereas farmers in the range $[-\bar{\theta}^{i}, -\hat{\theta}) \cup (\hat{\theta}, \bar{\theta}^{i}]$ adopt the service only for cost reduction and they always choose their default crops, regardless of the realized signal. See case (i) in Figure 6. Intuitively, the farmers in the middle range $[-\hat{\theta}, \hat{\theta}]$ have similar production costs for both crops, thus relying on the signal to choose a crop, in addition to enjoying the cost reduction feature. In contrast, farmers in $[-\bar{\theta}^{i}, -\hat{\theta}) \cup (\hat{\theta}, \bar{\theta}^{i}]$ are more specialized in growing one crop than another, and so they always stick to their default crops; nevertheless, because of the low adoption cost, they still choose to adopt agtech to benefit from its cost reduction feature. As the adoption cost K becomes higher, the adoption range shrinks to $[-\bar{\theta}^{ii}, \bar{\theta}^{ii}]$, and adopting agtech is worthwhile only when a farmer leverages both the yield prediction and cost reduction features. See case (ii) in Figure 6. Moreover, note that $\bar{K}$ is decreasing in market potential a. Thus, with a lower market potential a, case (i) is more likely to occur where some farmers adopt agtech for cost reduction but do not follow the signal to choose crops, as the low market potential may not justify the additional cost of growing a crop they are not specialized in.

We define shorthand notation $\bar{\theta} = \begin{cases} \bar{\theta}^i \text{ if } K \leq \bar{K} \\ \bar{\theta}^{ii} \text{ if } K > \bar{K} \end{cases}$ to capture both cases (i) and (ii) of Proposition 4. A larger $\bar{\theta}$ signifies a greater number of adopters (either for cost reduction or for both features), and a larger $\hat{\theta}$ indicates that there are more adopters following the yield prediction signal to choose crops, which will hereafter be referred to "prediction followers."

Proposition 5 presents some comparative statics results on how the two features influence the equilibrium outcome.

Proposition 5. *(i) Effect of Prediction Accuracy: The number of adopters is constant in prediction accuracy β if $K \leq \bar{K}$, but increasing in β if $K > \bar{K}$. A higher accuracy β always increases the number of prediction follower and the total supply of recommended crops. (ii)Effect of Cost Reduction Level: The number of adopters, prediction followers and the supply of recommended crops are always increasing in cost reduction level τ. (iii)Joint Effect of the Two Features: The two features can be substitutes, instead of complements, in determining farmers' crop choice, i.e., $\frac{\partial^2 q_1(H,L)}{\partial\beta\partial\tau} = \frac{\partial^2 q_2(L,H)}{\partial\beta\partial\tau} < 0$, a sufficient condition for which is $K \leq \bar{K}$ and $\tau > \bar{\tau}_1$.*

Different from Proposition 1, Proposition 5(i) shows that an increase in accuracy β will induce more farmers to adopt the service only if the adoption cost is sufficiently high, i.e., $K > \bar{K}$. This is because, as shown earlier, when $K \leq \bar{K}$, farmers at the indifference point of service adoption, i.e., $\theta = -\bar{\theta}^i$ and $\bar{\theta}^i$, leverage only the cost reduction feature. Consequently, the number of adopters is determined solely by the cost reduction feature, rather than the yield prediction feature. Additionally, we establish that an increase in accuracy β always results in more supply of recommended crops, as more farmers choose to follow the signal.

As shown in Proposition 5(ii), the effects of cost reduction level τ are intuitive. A higher level of cost reduction always induces more adopters. Moreover, it also increases the supply of recommended crops. This is because a higher τ lowers the production costs for both crops, thereby reducing the cost difference between crops for each farmer and making more farmers choose crops based on the signal.

The cost reduction feature has a complementary effect with the yield prediction feature, as a higher level of cost reduction makes it easier for farmers to switch crops in response to the signal. However, Proposition 5(iii) indicates that the two features are not always complementary in determining farmers' crop choice. If the adoption cost $K \leq \bar{K}$ and the cost reduction level τ is high enough, the two features can act as substitutes. In such cases, a further increase in τ will attract more farmers to adopt the service solely for cost reduction, and this weakens the effect of yield prediction accuracy β on the equilibrium quantities of recommended crops.

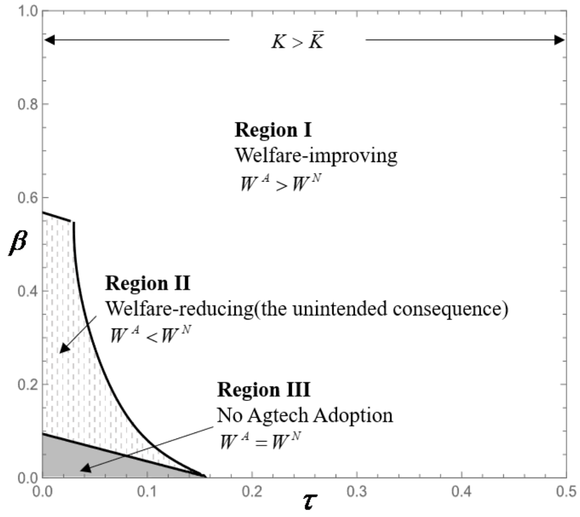
Similarly, we can express the farmer welfare when the cost reduction feature is considered; the details are shown in Appendix A2. Similar to the effect of the yield prediction feature, we find that a stronger cost reduction feature can also reduce welfare. In the following proposition, we analytically establish this result under a special case with simplifying assumptions, such as independent yield ($p_{HH} = 1/4$), perfect prediction ($\beta = 1$). Yet, we observe numerically that this unintended consequence arises over a broader range of parameter values.

Proposition 6. *The farmer welfare W^A can be decreasing in τ, for which a set of sufficient conditions are market potential $a < \bar{\bar{a}}$, $t > 1/2$, $K > \bar{K}$, $p_{HH} = 1/4$, $\mu = 0$, and $\beta = 1$.*

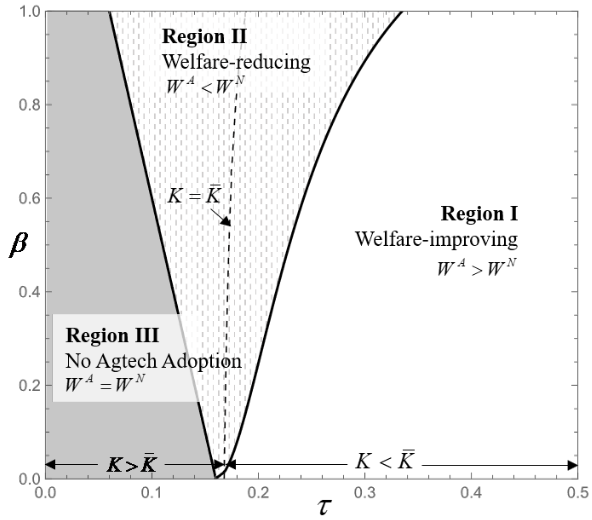
Although cost reduction is conventionally believed to be beneficial to farmers, our results indicate that when yield prediction and cost reduction features are offered as an integrated service, enhancement in the cost reduction feature may paradoxically reduce farmer welfare. This unintended consequence primarily stems from the interplay between the two features. Specifically, the cost reduction feature diminishes the cost difference between growing the two crops for each farmer, thereby incentivizing more farmers to switch crops based on the prediction signal. In markets with limited potential, the increase in the number of farmers growing the same crop and the improvement in expected yields lead to a significant drop in the clearing price. This price reduction can outweigh the gains from cost savings, ultimately reducing overall welfare.

Proposition 7. *For any (arbitrarily large) market potential a, there always exists a nonempty set of agtech parameters β and τ such that the introduction of agtech hurts the farmer welfare, i.e., $W^A < W^N$.*

As demonstrated in Proposition 7, when yield prediction and cost reduction features are considered simultaneously, the "unintended region" resulting from the service persists. Figure 7 presents a numerical illustration of the comparison between W^A and W^N for different market potentials. Details regarding the parameter calibration are illustrated in Appendix A1. In both cases, if the two feature parameters are low, no farmers will adopt the service and so $W^A = W^N$; see Region III in each panel of Figure 7. As the two parameters increase, some farmers (in the middle part of the Hotelling line) start to adopt the service, but the equilibrium may fall into Region II where $W^A < W^N$, i.e., the service reduces the overall welfare. We observe that the welfare-reducing region is larger and so the service is more likely to hurt farmer welfare when the



(a) High market potential (a = 5)



(b) Low market potential (a = 1.2)

Figure 7: Welfare implications of agtech given any combination of feature parameters [$p_{HH} = 0.4$, $t = 0.25$, $\mu = 0.5$, $K = 0.02$]

market potential is lower. More specifically, for the high market potential case in Figure 7(a), the service improves the welfare in most cases as long as the two parameters are high enough; see Region I. However, for the low market potential case in Figure 7(b), the service is more likely to be welfare-reducing as the yield prediction accuracy β is higher; see Region II in the upper part of the graph. This can be explained by Proposition 2 established earlier, which establishes that W^A is decreasing in β for sufficiently low market potential. We also observe that as the cost reduction level τ increases, the welfare-reducing region shrinks, because a larger τ has a direct benefit in reducing farmers' production costs and, moreover, it can mitigate the effect of accuracy β on production quantities and hence the competition intensity, which echoes the substitution effect of the two features in Proposition 5(iii).

Our findings indicate that to provide a welfare-improving agtech service, the feature parameters should be properly designed. For crops with high market potential, one should either not provide any technology, or offer sufficiently strong yield prediction and/or cost reduction features. A moderate level of features may hurt farmers if the parameters (β, τ) fall into the welfare-reducing region as shown in Figure 7(a). For crops with low market potential, the service should focus more on the cost reduction feature, as an excessively high accuracy of yield prediction can reduce the farmer welfare as shown in Figure 7(b).

Under some conditions, we can characterize the joint effect of the two feature parameters, as highlighted in Corollary 1.

Corollary 1. *Provided that all farmers adopt the service and yield correlation is low ($p_{HH} \leq \frac{1}{4\beta}$), there exists a threshold $\bar{\tau}$ such that W^A is increasing in β if and only if $\tau > \bar{\tau}$.*

Only when the level of cost reduction is high enough, enhancing the yield prediction accuracy β is welfare improving. As discussed earlier, an increase in β can reduce total welfare because it hurts the farmers who do not follow the yield prediction when choosing crops. A higher cost reduction level τ lowers production costs and also reduces the cost difference between crops, allowing more farmers to flexibly select crops based on yield information. Consequently, a sufficiently high τ can reverse the negative impact of β into a positive effect. Although Corollary 1 is proved under some technical conditions, our numerical study presented below shows that this insight holds for more general cases as well. More insights into the joint effect of the two features are also presented. The parameter calibration is provided in Appendix A1.

Example 3. (Joint Effect of Yield Prediction and Cost Reduction) Figure 8 illustrates the agtech-induced welfare changes ($W^A - W^N$) across different market potentials. The arrows indicate the direction of welfare improvement, while dark regions highlight welfare-reducing outcomes. We observe that the joint effect of prediction accuracy β and cost reduction τ heavily depends on the market potential, yielding the following key insights and policy implications:

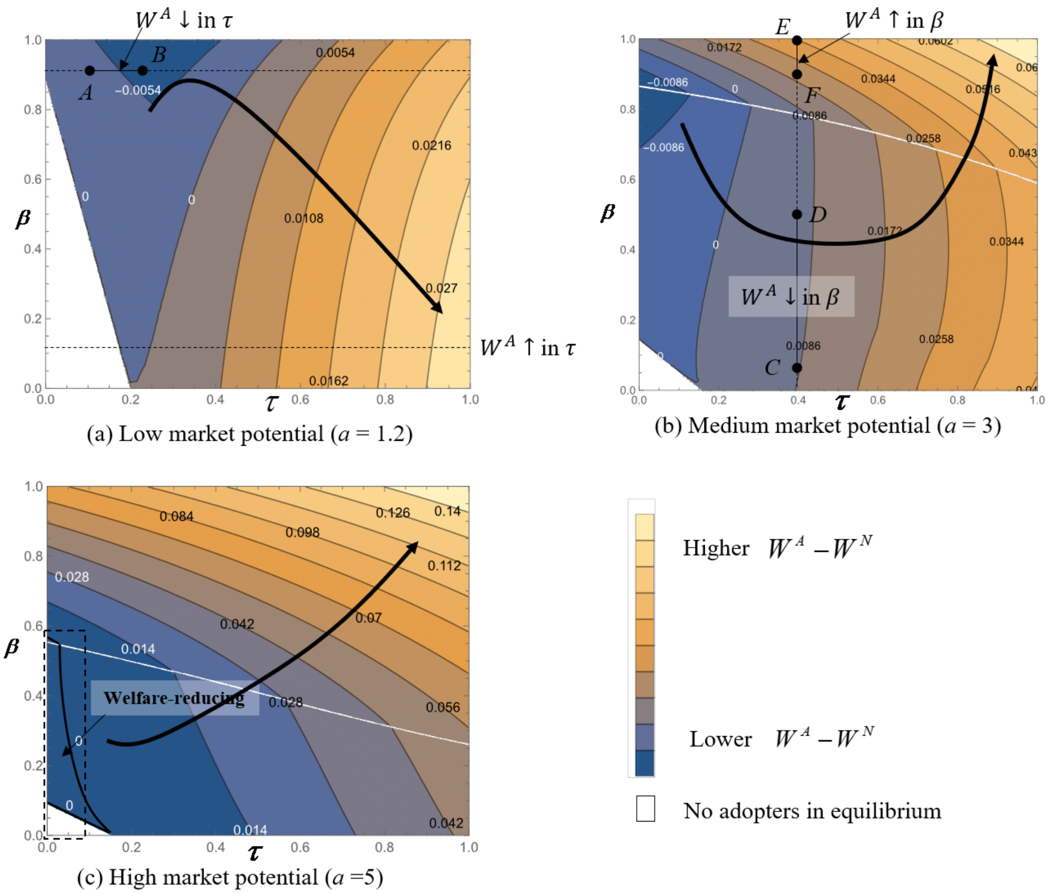


Figure 8: The agtech-induced welfare changes $W^A - W^N$ for different combinations of feature parameters (β, τ) [The arrow in each panel points to the direction where $W^A - W^N$ increases].

- **Low Market Potential (Figure 8a):** Simultaneously improving both features can inadvertently hurt farmers. While a higher β inherently reduces welfare, a greater τ can counterintuitively exacerbate this negative effect when β is high by inducing excessive adoption (Point A to B). Therefore, a welfare-improving service here should solely focus on maximizing cost reduction without offering yield prediction ($\beta = 0$, $\tau \to 1$).

- **Medium Market Potential (Figure 8b):** The impact of prediction accuracy depends crucially on the strength of cost reduction. If the achievable cost reduction is limited (e.g., $\tau < 0.4$), higher accuracy generally harms welfare (Point C to D); hence, investments should focus exclusively on strengthening τ. However, a sufficiently high cost reduction (e.g., $\tau \geq 0.8$) can counteract and reverse the negative effect of yield prediction, making enhancements in β valuable.

- **High Market Potential (Figure 8c):** Farmer welfare generally increases with both β and τ, meaning policymakers can safely improve both features simultaneously. Nevertheless, a small welfare-reducing region persists, echoing our earlier propositions.

Finally, we verify the impact of yield prediction on farmer income inequality in the presence of the cost reduction feature. The conclusions remain consistent with those derived from the base model; the details can be found in Appendix A4.

6 Extensions

We next investigate some extensions to verify the robustness of our main results and derive additional insights. In all these extensions, we incorporate both the yield prediction and cost reduction features. In the following, we present the primary findings from these extensions while presenting more detailed results and proofs in Appendix A3.

6.1 In-Season Monitoring and Contingent Intervention

Beyond the yield prediction and cost reduction features discussed in the base model, recent technological advancements enable real-time field monitoring, allowing farmers to adaptively adjust resource allocation and undertake interventions when necessary, thereby controlling costs and improving yields during the growing season. For example, real-time image diagnostics in maize fields, enabled by drone technology and computer vision analytics, allow immediate pest identification and remedial action, thereby preventing yield losses caused by diagnostic delays.[12]

[12] See `https://newsroom.ibm.com/IBM-watson?item=30660` accessed Aug 11, 2025

To model such technology-enabled in-season monitoring, we extend our model by allowing the agtech service to generate an updated in-season yield signal, denoted by s_i' if crop i is grown, in addition to the pre-season signal that informs crop selection. The in-season signal provides an updated prediction of crop yield based on information collected during the growing season, enabling farmers to decide whether to exert additional effort (or deploy additional resources) to improve yields. We hereafter refer to the provision of updated yield signals as the *in-season yield monitoring* feature of the agtech service. For tractability, we assume that the in-season signal is accurate in the sense that the realized s_i' always coincide with the actual yield level δ_i if no intervention is undertaken. If the updated signal is realized to be low ($s_i' = L$), farmers adopting the agtech service decide whether to undertake a corrective intervention at a given cost F. If taken, the intervention can restore the yield level from low to high, that is, from μ to 1, with success probability x, whereas it fails to improve yield with probability $1 - x$, where x captures the effectiveness of the additional effort. By contrast, if the updated signal is high ($s_i' = H$), we assume that intervention cannot further increase yield and is therefore unnecessary. This setting aligns with practice where agtech enables the early detection of adverse events such as pests, thus allowing for targeted interventions. Farmers who do not adopt the service do not receive any in-season signal; accordingly, signal-contingent intervention is not available to them.

Incorporating the possibility of in-season intervention, we modify the game sequence as follows: (i) Before the growing season, farmers decide whether to adopt the agtech service, and make crop choices as in our base model; (ii) during the growing season, contingent on the in-season signal s_i', agtech adopters decide whether to undertake an intervention; (iii) crops are harvested, and farmers receive their realized revenues.

The analysis becomes more involved, because to analyze adopters' in-season intervention decisions in stage (ii), we must consider various cases, depending on the realized pre-season signals and the resulting crop choices in stage (i). We relegate detailed technical discussions to Appendix A3.1. Despite the complexity, we managed to characterize adopters' intervention decisions in equilibrium. A mixed-strategy equilibrium may arise in which the adopters choose to intervene with some probability ρ. In our setting, ρ can represent the fraction of adopters who choose to intervene in equilibrium. Proposition 8 characterizes the equilibrium intervention probabilities ρ^*, where we allow for $\rho^* = 0$ or 1 when interventions are in pure strategies.

Proposition 8. *With the in-season yield monitoring feature, upon receiving an in-season low signal ($s_i' = L$) of the chosen crop, farmers' intervention probabilities $\rho^* \in [0, 1]$ depend on the pre-season signal and their crop choice, as described follow:*

(i) If $K \leq \bar{K}$ such that only a part of adopters follow the pre-season signal when choosing

crops (while the others do not follow), ρ^* for each farmer group is given as follows: Given symmetric pre-season signals (H, H) or (L, L), all adopters (including prediction followers and prediction nonfollowers) intervene with probability $\rho^* = \rho_s^i$; given asymmetric pre-season signals (H, L) or (L, H), prediction followers intervene with probability $\rho^* = \rho_{as}^i$, whereas prediction nonfollowers intervene with probability $\rho^* = \rho_{asc}^i$, where $\rho_{as}^i < \rho_s^i < \rho_{asc}^i$.

(ii) If $K > \bar{K}$ such that all adopters follow the pre-season signal, given symmetric pre-season signals (H, H) or (L, L), all adopters intervene with probability $\rho^* = \rho_s^{ii}$ for all adopters, while given asymmetric pre-season signals (H, L) or (L, H), all adopters intervene with probability $\rho^* = \rho_{as}^{ii}$, where $\rho_{as}^{ii} < \rho_s^{ii}$.

The equilibrium intervention probabilities vary across realizations of the pre-season signal and across adopter groups (depending on whether they follow the pre-season signal in their crop choices). For low adoption costs ($K \leq \bar{K}$), given asymmetric pre-season signals (H, L) or (L, H), prediction nonfollowers have a stronger incentive to intervene than followers, because asymmetric signals lead to oversupply of the recommended crop, reducing the marginal returns to intervention for those who follow the signal. For high adoption costs ($K > \bar{K}$) such that all adopting farmers follow the pre-season signal, interventions occur more frequently in equilibrium under symmetric signals (H, H) or (L, L).

Using the intervention equilibrium characterized above, we evaluate farmers' expected payoffs in the first stage and find that the in-season monitoring feature does not always improve welfare.

Proposition 9. *If the equilibrium intervention decisions constitute strictly mixed strategies across all situations under different pre-season signal (s_1, s_2), i.e., $\rho_l^k \in (0, 1)$ for all $l \in \{s, as, asc\}$ and $k \in \{i, ii\}$, the introduction of the in-season yield monitoring feature strictly decreases the profit of every farmer, thereby reducing overall farmer welfare.*

Proposition 9 shows that if only a subset of adopters chooses to intervene across all farmer groups and all scenarios characterized in Proposition 8, the in-season monitoring feature is welfare-reducing. The reason is as follows. Whenever a mixed-strategy equilibrium arises in the intervention stage, adopters are indifferent between intervening and not intervening; however, interventions by a subset of adopters depress market prices and thereby reduce the profits of non-adopters, leading to an overall welfare loss. Thus, our finding suggests that welfare may decline if the monitoring feature induces only limited intervention in equilibrium. Since interventions increase with the intervention effectiveness x, our result implies that the monitoring feature improves welfare only if farmers have sufficiently high intervention capability. As illustrated by Figure 9, when the intervention effectiveness x is small, no adopters choose to intervene, and therefore x has no impact on welfare. As x increases, it first reduces welfare as shown by the gray region in Figure 9; then, it starts to benefit welfare only when exceeding a certain threshold, since the in-season intervention alleviates the supply balance caused by pre-season yield prediction and benefits more adopters.

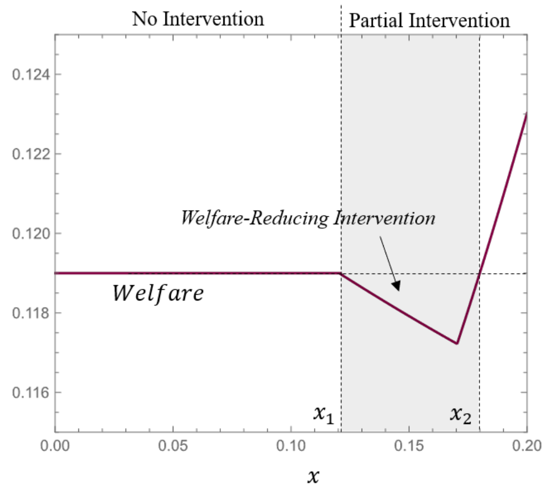


Figure 9: The effect of intervention effectiveness on welfare

Additionally, we present a numerical study in Appendix A3.1, which shows that the in-season intervention can mitigate income inequality. Overall, our analysis indicates that, like yield prediction and cost reduction features, the introduction of in-season monitoring may not necessarily improve farmer welfare.

6.2 More Than Two Crops

In this section, we demonstrate the robustness of our main results by analyzing a setting with three crop options based on a spokes model. For tractability, we assume that yields across the three crops are independent. Farmers are uniformly distributed on three spokes as shown in Figure 10. Each of the three endpoints represents the location of a crop. As in the base model, farmers closer to an endpoint have a lower production cost for growing the corresponding crop. We present the equilibrium results in Proposition 10.

Proposition 10. *Farmers' agtech service adoption and crop choice strategies fall into three cases. Consider farmers located in line OC_1.*

(i) When $0 < K < \bar{K}_1$, there exist thresholds $\bar{\theta}^i > \hat{\theta}_1 > \hat{\theta}_2$ in line OC_1. Farmers located in $[O, \bar{\theta}^i]$ adopt the service. Among adopters, those in $[O, \hat{\theta}_2]$ fully follow the signal when choosing crops (strict prediction followers); those in $[\hat{\theta}_2, \hat{\theta}_1]$ follow the signal only when it realizes as (L, H, H), and otherwise stick to their default crop choice (selective prediction followers); those in $[\hat{\theta}_1, \bar{\theta}^i]$ adopt the service solely for its cost reduction feature (prediction nonfollowers).

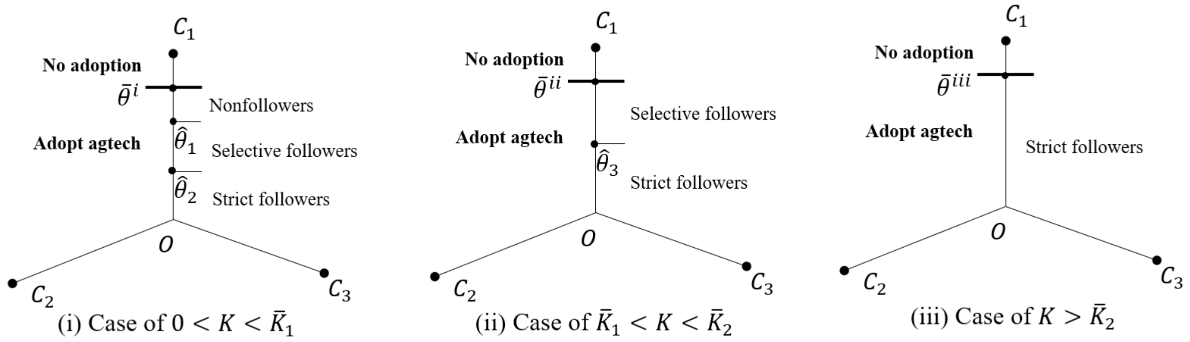


Figure 10: Segments of the farmers

(ii) When $\bar{K}_1 < K < \bar{K}_2$, there exist thresholds $\bar{\theta}^{ii} > \hat{\theta}_3$ in line OC_1. Farmers located in $[O, \bar{\theta}^{ii}]$ adopt the service. Among adopters, those in $[O, \hat{\theta}_3]$ fully follow the signal (strict prediction followers); those in $[\hat{\theta}_3, \bar{\theta}^{ii}]$ follow the signal only when it is (L, H, H), and otherwise adhere to their default crop choice (selective prediction followers).

(iii) When $K > \bar{K}_2$, there exists a threshold $\bar{\theta}^{iii}$ in line OC_1. Farmers located in $[O, \bar{\theta}^{iii}]$ adopt the service, and all adopters follow the signal in their crop choices (strict prediction followers).

Due to symmetry in the farmer distribution, farmers on segments OC_2 and OC_3 make decisions identical to those described above.

In the three-crop setting, the impact of yield predictions on farmers' crop choices remains similar to that in our base model, with more nuance arising regarding when farmers choose a recommended crop rather than their default option. Compared to the two-crop case, some farmers may follow the prediction selectively. That is, these farmers switch from their default choices only when the crop nearby is predicted as low yield while *both* alternative crops are predicted as high yield. Otherwise, they maintain their default choice. The intuition is as follows. If exactly one alternative crop is predicted to have a high yield, farmers anticipate a large surge in supply of that crop, leading to a substantial price decline, which makes switching unattractive. When both alternative crops are predicted to have high yield, the increased supply would be spread across the two, mitigating the price drop and making it more appealing to switch in response to the signal. In Appendix A3.2, we report a numerical study to examine the welfare implications in the three-crop setting. Consistent with the base model, higher predictive accuracy of the signal may reduce farmer welfare, and the negative effect is more pronounced when the market potential is small. In addition, when the market is sufficiently small, introducing the service generates lower welfare than the no-agtech benchmark.

6.3 False Positive Prediction Error

In our base model, yield predictions serve primarily as warnings of a low-yield state. Accordingly, the information structure is asymmetric: Predictions may generate false negatives (failing to warn of a low-yield state with probability $1 - \beta$) but involve no false positives (i.e., they never misclassify a high-yield state as low). To further verify the robustness of our core findings, we extend the model to incorporate both false negative and false positive errors. Specifically, for any state $\delta_i \in H, L$, the technology generates a correct signal $s_i = \delta_i$ with probability β, and an incorrect signal $s_i \neq \delta_i$ with probability $1 - \beta$. Under this symmetric information structure, an "L" signal no longer perfectly reveals a low-yield state. As presented in Appendix A3.3, our analysis shows that the market crowding effect driven by farmers' aggregate response to signals persists even under this more general informational environment, reinforcing the managerial insight that high-precision tools can paradoxically undermine farmer welfare.

6.4 Asymmetric Market Potentials

In the base model, we assume symmetric market potentials for both crops ($a_1 = a_2 = a$). In practice, market potentials may vary across different crops. To examine the robustness of our results, we extend the model to a setting with asymmetric market potentials: The market potential for crop 2 remains a, while that for crop 1 is $a + n$, where $n > 0$ represents the market size difference between the two crops.

Given that the market potential of one crop exceeds another, the indifference point for crop selection without agtech shifts from the middle of the Hotelling line to θ_N. As the effectiveness of yield prediction and cost reduction increases, farmers located near θ_N begin to adopt the service. Due to the analytical complexity introduced by this asymmetry – which exponentially increases the number of cases for threshold comparisons – we validate our findings through numerical experiments. The values of parameters are set similar as before and $a = 2$.

Figure 11(a) illustrates the impact of the asymmetric market potentials on farmers' adoption decisions, where farmers located within $\theta \in [\bar{\theta}_1, \bar{\theta}_2]$ adopt the service. When crop 1 has a larger market potential than crop 2, more farmers are inclined to choose crop 1. Moreover, we observe that the adoption interval $[\bar{\theta}_1, \bar{\theta}_2]$ expands as n increases. This is because, as crop 1 becomes more attractive, farmers located closer to crop 2 have a stronger incentive to access the yield prediction (to learn whether they should switch to crop 1) than those located closer to crop 1. Additionally, Figure 11(b) shows that under asymmetric market potentials, the introduction of the service can still reduce welfare as in our base model. In addition, we also observe that even with a large market potential, enhancements in both technology features (τ and β) can still lead

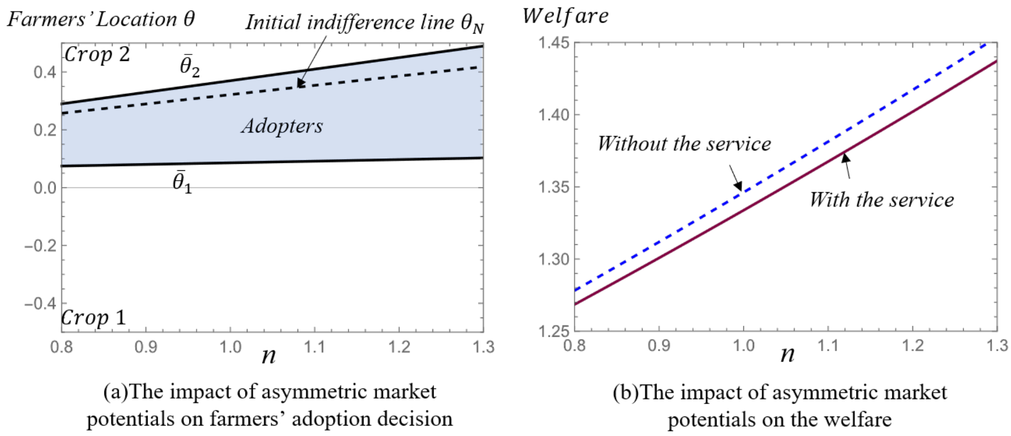


Figure 11: The impact of market advantage

to a reduction in welfare. These findings confirm that our main results remain robust. More details can be found in the Appendix A3.4.

7 Conclusion

Motivated by emerging agtech and its potential in improving farmers' income, we study how the two major benefits of agtech – yield prediction and cost reduction – influence smallholder farmers' welfare and income inequality. We show that farmer welfare can decrease with either the accuracy of yield prediction or the level of cost reduction, because the adoption of agtech may intensify competition in the market of recommended crops. Although this unintended consequence is more probable for crops with lower market potential, for any arbitrarily large market potential, there always exists a range of agtech parameters in which farmers are worse off as it is introduced. Furthermore, we relaxed some of the assumptions of the base model and found that the above results still hold. To improve welfare and address income inequality through offering agtech, our analysis uncovers the following caveats: (1) Simultaneously strengthening agtech features does not always improve welfare (i.e., yield prediction, cost reduction and yield enhancing); (2) enhancing yield prediction accuracy improves welfare only when crops have sufficiently high market potential or when the cost reduction feature is strong enough; (3) agtech does not always alleviate income inequality if it substantially hurt total welfare; and (4) in certain situations, increasing overall welfare and reducing income inequality may present conflicting goals.

Our findings offer profound policy implications. First, our results suggest that caution should be exercised when promoting emerging yield prediction technologies by reducing adoption costs (e.g., through financial subsidies) or by enhancing prediction capabilities (e.g., through investments that improve data accessibility, such as the USDA's support for open-access satellite data to monitor soil conditions). As shown in our analysis, such interventions may inadvertently lead to market crowding and ultimately harm farmers, especially for crops with limited market potential. Policymakers should carefully assess the impact of interventions that either lower adoption costs or improve prediction accuracy, rather than allowing prediction technologies to drive unchecked herding behavior.

Second, our findings show that existing technologies that lower farmers' growing costs or improve their operational efficiency can help offset the negative repercussions of yield prediction technologies. Promoting emerging predictive tools (e.g., yield forecasting software and related soil monitoring hardware) without simultaneously strengthening cost-reducing technologies (e.g., precision fertilizer applicators or automated irrigation systems) can be counterproductive for enhancing farmer welfare. As agtech services increasingly incorporate yield prediction features, policymakers should support both yield prediction and cost-reduction technologies in tandem to ensure an overall improvement in farmer welfare.

Third, our results reveal a "specialization trap" induced by yield prediction technology. While specialized farmers may appear more efficient, they are also more vulnerable, as they lack the flexibility to respond to yield signals. In contrast, nonspecialized farmers benefit from greater flexibility in crop choice. Accordingly, support for specialized farmers should shift away from "crop selection" advice toward "competitiveness-enhancing" measures (e.g., enhancing efficiency in production and distribution) that help them withstand intensified competition.

Finally, yield prediction may benefit nonspecialized farmers while eroding the income of specialized farmers. Even when the technology improves overall welfare, it may increase the Gini coefficient and widen income inequality across farmers. This creates a potential tension between maximizing welfare and minimizing inequality. For NGOs and governments concerned with poverty alleviation and equity, promoting advanced agtech in a uniform, one-size-fits-all manner across farmers may exacerbate income disparities. To better safeguard vulnerable farmer groups, policymakers may need to design targeted interventions, such as subsidies based on farmers' expertise or capabilities.

We have made several simplifying assumptions in the model, leading to a few directions for future research. First, although in a model extension we incorporate the role of agtech in helping farmers to improve yields during the growing season, one may examine more general settings with continuous-time monitoring or with heterogeneous farmer intervention capabilities. Furthermore, market demand information is also important for farmers' crop selection, and thus it is worth investigating a comprehensive model that considers the provision of both yield and demand information. Finally, farmers in our model are assumed to be risk-neutral, whereas in reality they may exhibit risk aversion; extending to more general risk attitudes is left for future research.

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Appendices

In this section, we provide the support materials and proofs of the main results of the paper.

A1 Calibration of Model Parameters in Numerical Study

We first calibrate farmers' production cost, which consists of two components: a common fixed cost C incurred by all farmers, and a heterogeneous variable cost t reflecting individual specialization levels. In modern grain production, land cost represents the single largest expenditure. According to the 2024 crop budgets released by the farmdoc project at the University of Illinois, the average cash rent for high-productivity farmland in Central Illinois is projected to be approximately \$250 per acre.[13] Beyond land, certain variable inputs function as "quasi-fixed" costs in practice. For instance, essential inputs like seeds and basic fertilizers are mandatory for achieving baseline yields, regardless of a farmer's technical proficiency. Specifically, the average cost of genetically modified (GM) corn seeds for 2025 is estimated at around \$150 per acre.[14] Furthermore, resource utilization efficiency (e.g., for pesticides, irrigation, and fertilizers) varies significantly with a farmer's specialization. Research from the University of Illinois indicates that the operating expense ratio fluctuates between 52% and 81%, with an average of 66%.[15] This implies a substantial efficiency gap: For the same revenue, low-efficiency farmers incur nearly 30% higher operating costs compared to their high-efficiency counterparts. Given that the contribution profit for corn is approximately \$400 per acre, implying a total revenue of around \$900–\$1,000 per acre, we normalize the possible revenue in a normal year to 1.[16] Based on this benchmark, we calibrate $C \approx 0.50$ to reflect the high proportion of fixed and quasi-fixed costs (land, seeds, etc.). To capture the significant real-world efficiency disparities, we set $t \in [0.20, 0.30]$, adopting a baseline value of $t = 0.25$. In addition, to reflect the current reality of thin or even negative profit margins in the agricultural sector, we set the lower bound of the market potential a in the range of 1.1 to 1.3 (Similar to Chintapalli and Tang, 2021). Finally, K denotes the fixed cost of technology adoption. Subscription fees for mainstream platforms like Climate FieldView Plus are approximately \$1,000 per farm (or \$3 per acre).[17] While hardware costs for drones, sensors, and smart displays are higher, the annualized cost amortized over multiple years ranges from \$8 to \$25 per acre.[18] Assuming a total revenue of \$1,000 per acre, the cost of a comprehensive service package (data + hardware amortization) is estimated at \$20–\$30 per acre. Consequently, we calibrate $K = 0.02$, representing a relatively low barrier to adoption.

Regarding yield uncertainty, the parameter μ represents the ratio of yield in the Low Yield State to that in the High Yield State. Historical data suggests that adverse conditions can trigger

[13]See `https://farmdocdaily.illinois.edu/2025/04/projected-farm-income-for-2025-importance-of-rental-arrangements-on-farm-income.htmlaccessedFeb12,2026`

[14]See `https://farmonaut.com/usa/corn-seed-cost-per-acre-corn-farming-profit-per-acre-2025accessedFeb12,2026`

[15]See `https://farmdocdaily.illinois.edu/2024/05/operational-ratios-for-evaluating-the-farm-business.html` accessed Feb 12, 2026

[16]See `https://www.ers.usda.gov/data-products/commodity-costs-and-returns` accessed Feb 12, 2026

[17]See `https://yieldmorebushels.com/climate-fieldview` accessed Feb 12, 2026

[18]See `https://farmonaut.com/precision-farming/agriculture-drone-services-pricing-near-me-2025-costs` accessed Feb 12, 2026

yield losses as high as 40%–50%[19], implying that μ can drop to 0.5 in specific localities. Taking the average level into account, we set $\mu = 0.7$. We define p_{HH} as the joint probability that both crops achieve high yields, capturing the inter-crop yield correlation. In the U.S. Midwest, corn and soybeans are typically grown in rotation on the same or adjacent plots, sharing identical solar radiation, temperature, and precipitation conditions. Accordingly, we assume $p_{HH} = 0.4$, which implies a correlation coefficient ρ of approximately 0.6, indicating a strong positive correlation.

A2 Proofs of Results of the Main Model

Proof of Proposition 1. Our model is solved by the backward induction. First, given the agtech adoption decisions of farmers, we analyze the decision of farmers' crop selection decisions. Then, we further consider the agtech adoption decisions and the welfare.

In the following, we list some probabilities we will use next.

Considering the yield prediction feature of agtech, there are four possible occurrences of the prediction signal, i.e., $(s_1, s_2) = (H, H)$, (H, L), (L, H), (L, L). Since agtech's predictions for the two crop yields are independent of each other and can correctly predict the bad outcome with probability β, thus, the possibilities of the four occurrences can be represented by

$$\Pr(s_1 = H, s_2 = H) = p_{HH} + p_{HL}\,(1-\beta) + p_{LH}\,(1-\beta) + p_{LL}(1-\beta)^2 = -\beta + \beta^2 p_{HH} + 1,$$

$$\Pr(s_1 = H, s_2 = L) = \Pr(s_1 = L, s_2 = H) = \beta p_{HL} + (1-\beta)\,\beta p_{LL} = \frac{1}{2}\left(\beta - 2\beta^2 p_{HH}\right),$$

$$\Pr(s_1 = L, s_2 = L) = \beta^2 p_{LL} = \beta^2 p_{HH}.$$

We can easily verify that $\Pr(s_1 = H, s_2 = H) + \Pr(s_1 = H, s_2 = L) + \Pr(s_1 = L, s_2 = H) + \Pr(s_1 = L, s_2 = L) = 1$.

Thus, the posterior probabilities of yields of two crops can be obtained by Bayes' rule:

$$\eta_i(s_1, s_2) = \Pr(\delta_i = H | s_1, s_2) = \frac{\Pr(\delta_i = H)\Pr(s_1, s_2 | \delta_i = H)}{\Pr(s_1, s_2)},$$

$$\eta_1(H, H) = \eta_2(H, H) = \frac{p_{HH} + p_{HL}\,(1-\beta)}{\Pr(s_1 = H, s_2 = H)} = \frac{-\beta + 2\beta p_{\mathrm{HH}} + 1}{-2\beta + 2\beta^2 p_{\mathrm{HH}} + 2}.$$

Similarly, we have

$$\eta_1(H, L) = \eta_2(L, H) = \frac{1 - 2p_{\mathrm{HH}}}{1 - 2\beta p_{\mathrm{HH}}} = \frac{1 - 2p_{\mathrm{HH}}}{1 - 2\beta p_{\mathrm{HH}}},$$

$$\eta_1(L, L) = \eta_2(L, L) = \eta_1(L, H) = \eta_2(H, L) = 0.$$

Next, we can represent the expected yields of farmers using agtech after receiving the agtech signal, which are

$$\mathbb{E}(z_1 \,| H, L) = \mathbb{E}(z_2 \,| L, H) = \mu\,(1 - \eta_1(H, L)) + \eta_1(H, L) = \frac{2((\beta-1)\mu + 1)p_{\mathrm{HH}} - 1}{2\beta p_{\mathrm{HH}} - 1}.$$

[19]See `https://corn.ces.ncsu.edu/corn-production-information/the-impact-of-early-drought-on-corn-yield/` accessed Feb 12, 2026

Similarly,

$$\mathbb{E}(z_2\,|H,L\,) = \mathbb{E}(z_1\,|L,H\,) = \mathbb{E}(z_2\,|L,L\,) = \mathbb{E}(z_2\,|L,L\,) = \mu,$$

$$\mathbb{E}(z_1\,|H,H\,) = \mathbb{E}(z_2\,|H,H\,) = \frac{2((\beta-1)\beta\mu+\beta)p_{\mathrm{HH}} - (\beta-1)(\mu+1)}{-2\beta+2\beta^2 p_{\mathrm{HH}}+2}.$$

Furthermore, we can obtain $\mathbb{E}(z_i^2\,|s_1,s_2\,)$ as follows.

$$\mathbb{E}(z_1^2\,|H,L\,) = \mathbb{E}(z_2^2\,|L,H\,) = \eta_1(H,L) + (1-\eta_1(H,L))\,\mu^2 = \frac{2\left((\beta-1)\mu^2+1\right)p_{\mathrm{HH}}-1}{2\beta p_{\mathrm{HH}}-1},$$

$$\mathbb{E}(z_2^2\,|H,L\,) = \mathbb{E}(z_1^2\,|L,H\,) = \eta_2(H,L) + (1-\eta_2(H,L))\,\mu^2 = \mu^2.$$

Similarly,

$$\mathbb{E}(z_1^2\,|H,H\,) = \mathbb{E}(z_2^2\,|H,H\,) = \frac{2\left((\beta-1)\beta\mu^2+\beta\right)p_{\mathrm{HH}} - (\beta-1)\left(\mu^2+1\right)}{-2\beta+2\beta^2 p_{\mathrm{HH}}+2},$$

$$\mathbb{E}(z_1^2\,|L,L\,) = \mathbb{E}(z_2^2\,|L,L\,) = \mu^2.$$

Then we can obtain the expected profits of the farmer at location θ receiving the signal:

$$\mathbb{E}(\pi_1\,|s_1,s_2\,) = a\mathbb{E}(z_1\,|s_1,s_2\,) - \mathbb{E}(z_1^2\,|s_1,s_2\,)q_1(H,H) - K - t\left(\theta+\frac{1}{2}\right) - C,$$

$$\mathbb{E}(\pi_2\,|s_1,s_2\,) = a\mathbb{E}(z_2\,|s_1,s_2\,) - \mathbb{E}(z_2^2\,|s_1,s_2\,)q_2(H,H) - K - t\left(-\theta+\frac{1}{2}\right) - C.$$

Specifically, the expected profits of the farmer at location θ using agtech in the case with different agtech signals can be shown as

$$\begin{aligned}\mathbb{E}(\pi_1\,|H,H\,) = {} & \frac{\beta p_{\mathrm{HH}}\left(-2a((\beta-1)\mu+1)+2(\beta-1)\mu^2 q_1(H,H)+2q_1(H,H)+\beta(2\theta+1)t\right)}{2\beta-2\beta^2 p_{\mathrm{HH}}-2}\\ & + \frac{2\beta^2 p_{\mathrm{HH}}K+(\beta-1)\left(a\mu+a-2K+\mu^2(-q_1(H,H))-q_1(H,H)-2\theta t-t\right)}{2\beta-2\beta^2 p_{\mathrm{HH}}-2} - C,\end{aligned}$$

$$\begin{aligned}\mathbb{E}(\pi_2\,|H,H\,) = {} & \frac{\beta p_{\mathrm{HH}}\left(2a((\beta-1)\mu+1)-\beta(2K+(1-2\theta)t)-2q_2(H,H)\left((\beta-1)\mu^2+1\right)\right)}{-2\beta+2\beta^2 p_{\mathrm{HH}}+2}\\ & - \frac{(\beta-1)\left(a\mu+a-2K+\mu^2(-q_2(H,H))-q_2(H,H)+2\theta t-t\right)}{-2\beta+2\beta^2 p_{\mathrm{HH}}+2} - C,\end{aligned}$$

$$\begin{aligned}\mathbb{E}(\pi_1\,|H,L\,) = {} & \frac{p_{\mathrm{HH}}\left(4a((\beta-1)\mu+1)\right)-2a+2K+2q_1(H,L)+(2\theta+1)t}{4\beta p_{\mathrm{HH}}-2}\\ & - \frac{2p_{\mathrm{HH}}\left(\left(2\beta K+2(\beta-1)\mu^2 q_1(H,L)+2q_1(H,L)+\beta(2\theta+1)t\right)\right)}{4\beta p_{\mathrm{HH}}-2} - C,\end{aligned}$$

$$\begin{aligned}\mathbb{E}(\pi_2\,|L,H\,) = {} & \frac{p_{\mathrm{HH}}\left(4a((\beta-1)\mu+1)\right)-2a+2K+2q_2(L,H)-2\theta t+t}{4\beta p_{\mathrm{HH}}-2}\\ & - \frac{2p_{\mathrm{HH}}\left(2\left(2\beta K+2(\beta-1)\mu^2 q_2(L,H)+2q_2(L,H)+\beta(1-2\theta)t\right)\right)}{4\beta p_{\mathrm{HH}}-2} - C,\end{aligned}$$

$$\mathbb{E}(\pi_2\,|H,L\,) = a\mu - K + \mu^2(-q_2(H,L)) + \theta t - \frac{t}{2} - C,$$

$$\mathbb{E}(\pi_1 \,|L,H\,) = a\mu - K + \mu^2(-q_1(H,L)) - \left(\theta + \frac{1}{2}\right)t - C,$$

$$\mathbb{E}(\pi_1 \,|L,L\,) = a\mu - K + \mu^2(-q_1(L,L)) - \left(\theta + \frac{1}{2}\right)t - C,$$

$$\mathbb{E}(\pi_2 \,|L,L\,) = a\mu - K + \mu^2(-q_2(L,L)) + \theta t - \frac{t}{2} - C.$$

Next, by the backward induction, we try to obtain the threshold of farmers' crop choices:

If a farmer does not use agtech or agtech is not introduced to the market, it is easy to find that he will choose crop 1 if $\theta < 0$. Otherwise, he will choose crop 2.

If a farmer uses agtech, he will plant the crop based on the considering of the signal and his expected profits.

We first prove that under symmetric signal realizations (H,H) and (L,L), the crop selection indifference point for adopters is exactly the market center, i.e., $\hat{\theta}(H,H) = 0$ and $\hat{\theta}(L,L) = 0$.

We prove this by using the rational expectations equilibrium conditions. Assume the adoption region be $[-\bar{\theta}, \bar{\theta}]$, $\bar{\theta} > 0$. We analyze the (L,L) case as an example. Suppose, by contradiction, that the indifference point is $\hat{\theta}(L,L) = \theta^* \neq 0$. Without loss of generality, assume $\theta^* > 0$. Under this assumption, agtech adopters in the interval $[-\bar{\theta}, \theta^*]$ will plant crop 1, and those in $[\theta^*, \bar{\theta}]$ will plant crop 2. Cause the non-adopters' decision threshold remains at 0 due to the symmetric prior, the total expected numbers of farmers planting crop i are: $q_1(L,L) = \int_{-\bar{\theta}}^{\theta^*} f(\theta)d\theta + q_1^N(L,L) = \theta^* + \bar{\theta} + \frac{1}{2}$, $q_2(L,L) = \int_{\theta^*}^{\bar{\theta}} f(\theta)d\theta + q_2^N(L,L) = \bar{\theta} - \theta^* + \frac{1}{2}$. Thus, the difference in market quantities is driven entirely by the adopters: $q_1(L,L) - q_2(L,L) = (\theta^* + \bar{\theta}) - (\bar{\theta} - \theta^*) = 2\theta^* > 0$, which implies $q_1(L,L) > q_2(L,L)$. However, recall the indifference condition derived by $\mathbb{E}(\pi_1 \,|L,L\,) = \mathbb{E}(\pi_2 \,|L,L\,)$ is $\theta^* = \frac{\mu^2(q_2(L,L) - q_1(L,L))}{2t}$. If $q_1(L,L) > q_2(L,L)$, then the right-hand side is strictly negative, meaning $\theta^* < 0$. This contradicts our initial assumption that $\theta^* > 0$. A symmetric contradiction arises if we assume $\theta^* < 0$. Therefore, the only fixed point that satisfies the rational expectations equilibrium is $\theta^* = 0$. By the exact same symmetry logic, $\hat{\theta}(H,H) = 0$.

Next, consider the case under asymmetric signal realizations (H,L) and (L,H). Recall that location $\bar{\theta}$ captures the farmer who is indifferent between adopting agtech and not adopting. Since $\bar{\theta} > 0$, this farmer inherently has a comparative advantage in growing crop 2. If this farmer chooses not to adopt agtech, they will plant crop 2 based on their prior. If this marginal farmer adopts agtech, they pay the cost K. The technology only holds economic value if it can alter their prior planting decision. Specifically, when receiving the (H,L) signal, the expected yield of crop 1 is significantly higher than crop 2, compelling the farmer to switch from crop 2 to crop 1. If the farmer still plants crop 2 even under the (H,L) signal, the agtech provides zero actionable value and the farmer would never incur the cost K. Therefore, for the adopter at $\bar{\theta}$, the (H,L) signal represents the exact boundary condition where switching to crop 1 is profitable. Mathematically, this forces all the farmers located in $[-\bar{\theta}, \theta]$ will select crop to grow base on the signal.

Next, by comparing the expected incomes of farmers adopting or not adopting agtech, we can obtain the farmers' agtech adoption decisions, which is associated with the threshold $\bar{\theta}$.

If a farmer at location θ adopts the agtech, conditional on realized signal (s_1, s_2), his expected profit is given by

$$\mathbb{E}(\pi_i|s_1,s_2) = a\mathbb{E}(z_i|s_1,s_2) - q_i(s_1,s_2)\mathbb{E}(z_i^2|s_1,s_2) - c_i(\theta) - K.$$

When a farmer receives a signal (s_1, s_2), he can select a crop with higher expected profit. Hence, his anti-expected profit is given by

$$U_A = \sum_{s_1,s_2\in\{H,L\}} \Pr(s_1,s_2) \max_{i\in\{1,2\}} \mathbb{E}(\pi_i|s_1,s_2).$$

If a farmer at location θ does not adopt agtech, he can also estimate the probability of agtech giving four signals $\Pr(s_1, s_2)$, and then estimate his expected yield and market crop quantity under each signal. However, he does not know what the specific signal is, so he cannot modify his planting decision according to the signal. Thus his profit can be expressed as follows.

First, he can estimate his profit planting crop i under four signals:

$$\mathbb{E}(\pi_i^N|s_1,s_2) = a\mathbb{E}(z_i|s_1,s_2) - q_i(s_1,s_2)\mathbb{E}(z_i^2|s_1,s_2) - c_i(\theta).$$

Then, he can estimate his expected profit:

$$\mathbb{E}(\pi_i^N) = \sum_{s_1,s_2\in\{H,L\}} \Pr(s_1,s_2)\mathbb{E}(\pi_i^N|s_1,s_2).$$

Hence, his anti-expected profit is given by

$$U_N = \max_{i\in\{1,2\}} \mathbb{E}(\pi_i^N).$$

Consider the right side of the Hotelling line as an example, recall that all the farmers adopting agtech will choose a crop according to the signal. Thus, the quantities of farmers planting crop i in the market is determined by the threshold $\bar{\theta}$, i.e., $q_1(H,L) = q_2(L,H) = \bar{\theta} + \frac{1}{2}; q_2(H,L) = q_1(L,H) = \frac{1}{2} - \bar{\theta}; q_1(H,H) = q_2(H,H) = q_1(L,L) = q_2(L,L) = \frac{1}{2}$.

Thus, taking the farmers located at the right of the Hotelling line as an example, if the farmers adopt agtech, then he will select crop 1 when he receives a signal (H, L). Otherwise, he will plant crop 2. Thus, his income can be represented by

$$\begin{aligned}
U_A = &\Pr(s_1 = H, s_2 = L)\left(a\mathbb{E}(z_1\,|H,L) - \mathbb{E}(z_1^2\,|H,L)q_1(H,L) - \left(\theta + \frac{1}{2}\right)t\right) \\
&+ \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_2\,|H,H) - \mathbb{E}(z_2^2\,|H,H)q_2(H,H) - \left(\frac{1}{2} - \theta\right)t\right) \\
&+ \Pr(s_1 = L, s_2 = H)\left(a\mathbb{E}(z_2\,|L,H) - \mathbb{E}(z_2^2\,|L,H)q_2(L,H) - \left(\frac{1}{2} - \theta\right)t\right) \\
&+ \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_2\,|L,L) - \mathbb{E}(z_2^2\,|L,L)q_2(L,L) - \left(\frac{1}{2} - \theta\right)t\right) - K - C,
\end{aligned}$$

$$
\begin{aligned}
U_N = &\Pr(s_1 = H, s_2 = H)(a\mathbb{E}(z_2\,|H,H\,) - \mathbb{E}(z_2^2\,|H,H\,)q_2(H,H)) \\
&+ \Pr(s_1 = H, s_2 = L)(a\mathbb{E}(z_2\,|H,L\,) - \mathbb{E}(z_2^2\,|H,L\,)q_2(H,L)) \\
&+ \Pr(s_1 = L, s_2 = H)(a\mathbb{E}(z_2\,|L,H\,) - \mathbb{E}(z_2^2\,|L,H\,)q_2(L,L)) \\
&+ \Pr(s_1 = L, s_2 = L)(a\mathbb{E}(z_2\,|L,L\,) - \mathbb{E}(z_2^2\,|L,L\,)q_2(L,L)) - \left(\frac{1}{2} - \theta\right)t - C.
\end{aligned}
$$

Similarly, solving $U_A = U_N$, we have the threshold

$$
\bar{\theta} = \frac{2a\beta\mu - 2a\beta - 2\beta(\mu-1)(2a-\mu-1)p_{\mathrm{HH}} - \beta\mu^2 + \beta + 4K}{4\beta p_{\mathrm{HH}}\left((2\beta-1)\mu^2 + 2\beta t + 1\right) - 2\left(\beta\left(\mu^2+1\right) + 2t((\beta-1)+1)\right)}.
$$

Similarly, we can obtain the threshold in the left of the Hotelling line.

We can obtain the number of adopters by: $\bar{\theta}$, i.e., $q_1(H,L) = q_2(L,H) = \bar{\theta} + \frac{1}{2}; q_2(H,L) = q_1(L,H) = \frac{1}{2} - \bar{\theta}; q_1(H,H) = q_2(H,H) = q_1(L,L) = q_2(L,L) = \frac{1}{2}$.

Next, consider the effect of prediction accuracy β on the threshold $\bar{\theta}$, which determine the number of adopters and the total supply of recommended crops. Directly verifying the sign of $\frac{\partial\bar{\theta}}{\partial\beta}$ is complex. Instead, we analyze it using the Implicit Function Theorem based on the marginal adopter's indifference condition. We focus on the farmers located on the right side of the Hotelling line as an example (Since farmers are symmetrically distributed on the Hotelling line, the results can be extended to the global). Consider the farmer located to the right of $\bar{\theta}$ and infinitely close to $\bar{\theta}$ ($\theta \to \bar{\theta}^+$), which means his income without agtech is really close to the income with agtech, i.e., $\mathbb{E}\left(\pi_{\theta\to\bar{\theta}^+}\right)_A = \mathbb{E}\left(\pi_{\theta\to\bar{\theta}^+}\right)_N$. Notice that his income with agtech is

$$
\mathbb{E}\left(\pi_\theta\right)_A = \frac{1}{4}\begin{pmatrix} 2a(\beta(-\mu) + \beta + \mu + 1) - 4\beta\theta + \beta\mu^2 - \beta - 4K - \mu^2 + 4\theta t - 2t - 1 \\ 2\beta p_{\mathrm{HH}}\left(2a(\mu-1) - \mu^2 + 4\theta\left((\beta-1)\mu^2 + \beta t + 1\right) + 1\right) - 4\beta\theta t \end{pmatrix} - C.
$$

His income without agtech is

$$
\mathbb{E}\left(\pi_\theta\right)_N = \frac{1}{4}\left(2a(\mu+1) + 2\beta\theta\mu^2 - 2\beta\theta - 4\beta\theta\left(\mu^2-1\right)p_{\mathrm{HH}} - \mu^2 + 4\theta t - 2t - 1\right) - C.
$$

It should be noticed that $\frac{\partial[\mathbb{E}(\pi_\theta)_A - \mathbb{E}(\pi_\theta)_N]}{\partial\theta} = -\frac{1}{2}\beta\left(\mu^2+1\right) + \beta p_{\mathrm{HH}}\left((2\beta-1)\mu^2 + 2\beta t + 1\right) - \beta t < 0$, which means as θ increases, $\frac{\partial[\mathbb{E}(\pi_\theta)_A - \mathbb{E}(\pi_\theta)_N]}{\partial\theta}$ will decrease. Now consider the effect of parameter β, we find that
$\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta} = \frac{1}{4}\left(2p_{\mathrm{HH}}\left(2a(\mu-1) - \mu^2 + \theta\left((8\beta-4)\mu^2 + 8\beta t + 4\right) + 1\right) - 2a(\mu-1)\right)$
$+\frac{1}{4}\left(-4\theta + \mu^2 - 4\theta t - 1\right)$. In addition, we find $\frac{\partial\mathbb{E}(\pi_\theta)_N}{\partial\beta} = -\frac{1}{2}\theta\left(\mu^2-1\right)(2p_{\mathrm{HH}}-1) < 0$ is always true. Thus, when $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta} > 0$, i.e., when
$\left(2p_{\mathrm{HH}}\left(2a(\mu-1) - \mu^2 + \theta\left((8\beta-4)\mu^2 + 8\beta t + 4\right) + 1\right) - 2a(\mu-1)\right) + \left(-4\theta + \mu^2 - 4\theta t - 1\right) > 0$, as β increases, the farmer's income with agtech will increase but his income without agtech will decrease, which means $\mathbb{E}\left(\pi_\theta\right)_A > \mathbb{E}\left(\pi_\theta\right)_N$, thus he will prefer to adopt agtech. More farmers intend to use the service and the threshold $\bar{\theta}$ will move right. The above results means that in the situation that $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta} > 0$, $\frac{\partial\bar{\theta}}{\partial\beta} > 0$ always holds.

Now we consider the situation $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta} < 0$. In that case, both $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta}$ and $\frac{\partial\mathbb{E}(\pi_\theta)_N}{\partial\beta}$ are negative. We can prove that $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta} - \frac{\partial\mathbb{E}(\pi_\theta)_N}{\partial\beta} > 0$ to verify the result. We have $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta} - \frac{\partial\mathbb{E}(\pi_\theta)_N}{\partial\beta} = \frac{1}{4}\left(4a(\mu-1)p_{\mathrm{HH}} - 2a(\mu-1) - 2\mu^2 p_{\mathrm{HH}} + 2p_{\mathrm{HH}} + \mu^2 - 1\right)$

$+\frac{1}{4}\theta\left(2p_{\mathrm{HH}}\left((8\beta-2)\mu^2+8\beta t+2\right)-2\mu^2-4t-2\right)$. Solve $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta}-\frac{\partial\mathbb{E}(\pi_\theta)_N}{\partial\beta}=0$, we have $\theta_K=-\frac{(\mu-1)(2a-\mu-1)(2p_{\mathrm{HH}}-1)}{4p_{\mathrm{HH}}((4\beta-1)\mu^2+4\beta t+1)-2(\mu^2+2t+1)}$. It is easily to verify that in the situation where $2p_{\mathrm{HH}}\left((8\beta-2)\mu^2+8\beta t+2\right)-2\mu^2-4t-2>0$, when $\theta>\theta_K$, we have $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta}-\frac{\partial\mathbb{E}(\pi_\theta)_N}{\partial\beta}>0$. Since in that case $\theta_K<0$ always holds. Thus, in this situation, the effect of β is proved. In the situation where $2p_{\mathrm{HH}}\left((8\beta-2)\mu^2+8\beta t+2\right)-2\mu^2-4t-2<0$, when $\theta<\theta_K$, we have $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta}-\frac{\partial\mathbb{E}(\pi_\theta)_N}{\partial\beta}>0$. It is easily to check that $\bar{\theta}\leq\bar{\theta}(K=0)=-\frac{(\mu-1)(2a-\mu-1)(2p_{\mathrm{HH}}-1)}{p_{\mathrm{HH}}((8\beta-4)\mu^2+8\beta t+4)-2(\mu^2+2t+1)}$. It should be noticed that

$$\begin{aligned}&\left[4p_{\mathrm{HH}}((4\beta-1)\mu^2+4\beta t+1)-2(\mu^2+2t+1)\right]\\&-\left[p_{\mathrm{HH}}((8\beta-4)\mu^2+8\beta t+4)-2(\mu^2+2t+1)\right]=8\beta p_{\mathrm{HH}}(\mu^2+t)>0.\end{aligned}$$

Thus, $\bar{\theta}<\bar{\theta}(K=0)<\theta_K$. Thus, if the farmer located at θ close to $\bar{\theta}$, we have $\theta<\theta_K$, which means $\frac{\partial\mathbb{E}(\pi_\theta)_A}{\partial\beta}-\frac{\partial\mathbb{E}(\pi_\theta)_N}{\partial\beta}>0$ always holds. Thus, similarly, though as β increases, $\mathbb{E}\left(\pi_\theta\right)_A$ and $\mathbb{E}\left(\pi_\theta\right)_N$ both decrease, the former decreased less than the latter. Therefore, its better for the farmer located at θ to adopt agtech, which means more farmers will adopt agtech, i.e., $\frac{\partial\bar{\theta}}{\partial\beta}>0$. In summary, we can prove that $\frac{\partial\bar{\theta}}{\partial\beta}>0$ always holds true within the domain of definition when $K>\bar{K}$, the result is proved.■

Proof of Proposition 2. In our model, the whole welfare in our model is

$$W=\int_{-0.5}^{0.5}\pi^*(\theta)d\theta.$$

When agtech is not introduced to the market, the farmers located at the right of the Hotelling line will plant crop 2 and the farmers located at the left of the line will plant crop 1. Thus, we can easily obtain the welfare when agtech is not introduced to the market, which is

$$W^N=\frac{1}{2}\left(a-\frac{1}{2}b\right)+\frac{1}{2}\mu\left(a-\frac{1}{2}b\mu\right)-\frac{1}{4}t-C.$$

When agtech is introduced, the result is more complex. The farmers' ex-ante welfare can be represented by

$$W^A=2\left[\int_{-0.5}^{-\bar{\theta}}U_n(\theta)d\theta+\int_{-\bar{\theta}}^{0}U_{acy}(\theta)d\theta\right].$$

where $U_n(\theta)$ and U_{acy} are the expected profits of each nonadopter and adopter, respectively, as functions of θ. Since the Hotelling line is symmetrical, we can use the profit of farmers located on the left of the Hotelling line as an example:

$$\begin{aligned}U_n(\theta)=&\Pr(s_1=H,s_2=L)\left(a\mathbb{E}(z_1\,|H,L)-\mathbb{E}(z_1^2\,|H,L)q_1(H,L)\right)\\&+\Pr(s_1=L,s_2=H)\left(a\mathbb{E}(z_1\,|L,H)-\mathbb{E}(z_1^2\,|L,H)q_1(L,H)\right)\\&+\Pr(s_1=H,s_2=H)\left(a\mathbb{E}(z_1\,|H,H)-\frac{\mathbb{E}(z_1^2\,|H,H)}{2}\right)\\&+\Pr(s_1=L,s_2=L)\left(a\mathbb{E}(z_1\,|L,L)-\frac{\mathbb{E}(z_1^2\,|L,L)}{2}\right)-\left(\theta+\frac{1}{2}\right)t-C,\end{aligned}$$

$$
\begin{aligned}
U_{acy}(\theta) = & \Pr(s_1 = H, s_2 = L)\left(a\mathbb{E}(z_1\,|H,L) - \mathbb{E}(z_1^2\,|H,L)q_1(H,L) - t(\frac{1}{2}+\theta)\right)\\
& + \Pr(s_1 = L, s_2 = H)\left(a\mathbb{E}(z_1\,|L,H) - \mathbb{E}(z_1^2\,|L,H)q_2(L,H) - t(\frac{1}{2}-\theta)\right)\\
& + \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_1\,|H,H) - \frac{\mathbb{E}(z_1^2\,|H,H)}{2} - t(\frac{1}{2}+\theta)\right)\\
& + \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_1\,|L,L) - \frac{\mathbb{E}(z_1^2\,|L,L)}{2} - t(\frac{1}{2}+\theta)\right) - K - C.
\end{aligned}
$$

Since the two crops are symmetrical, we have $\mathbb{E}(z_1\,|H,L) = \mathbb{E}(z_2\,|L,H)$, $\mathbb{E}(z_1^2\,|H,L) = \mathbb{E}(z_2^2\,|L,H)$, $\Pr(s_1 = H, s_2 = H) + \Pr(s_1 = H, s_2 = L) + \Pr(s_1 = L, s_2 = H) + \Pr(s_1 = L, s_2 = L) = 1$, the above equation can be rearranged as follows (it should be noticed that we omit the details of the equation because the original equation is too complex).

$$
\begin{aligned}
W^A = & \Pr(s_1 = H, s_2 = L)\left(2\bar{\theta}+1\right)\left(a\mathbb{E}(z_1\,|H,L) - \mathbb{E}(z_1^2\,|H,L)\left(\bar{\theta}+\frac{1}{2}\right)\right)\\
& + \Pr(s_1 = L, s_2 = H)\left(1-2\bar{\theta}\right)\left(a\mathbb{E}(z_1\,|L,H) - \mathbb{E}(z_1^2\,|L,H)\left(\frac{1}{2}-\bar{\theta}\right)\right)\\
& + (1 - 2\Pr(s_1 = L, s_2 = H))t\bar{\theta}^2 - t\bar{\theta}^2 + \bar{\theta}(t - 2K)\\
& + \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_1\,|H,H) - \frac{\mathbb{E}(z_1^2\,|H,H)}{2}\right)\\
& + \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_1\,|L,L) - \frac{\mathbb{E}(z_1^2\,|L,L)}{2}\right) - \frac{t}{4} - C.
\end{aligned}
$$

Bring the details of $\mathbb{E}(z_1\,|H,L)$, $\mathbb{E}(z_1^2\,|H,L)$, $\Pr(s_1 = H, s_2 = H)$, $\Pr(s_1 = H, s_2 = L)$, $\Pr(s_1 = L, s_2 = H)$, $\Pr(s_1 = L, s_2 = L)$, as well as $\bar{\theta}$ back to the equation, we can obtain the final welfare (which is omit here).

Considering the direct effect of the features of precision agriculture, given $\bar{\theta}$, we have $\frac{\partial W^A}{\partial \beta} = \bar{\theta}\left(2\bar{\theta}p_{\mathrm{HH}}\left((4\beta-1)\mu^2 + 2\beta t + 1\right) - \left(\bar{\theta}\left(\mu^2+t+1\right)\right) + (\mu-1)(a-\mu-1)\left(2p_{\mathrm{HH}}-1\right)\right)$, and the threshold $\bar{a}_k = \frac{\bar{\theta}(\mu^2+1-8\beta\mu^2 p_{\mathrm{HH}}+2\mu^2 p_{\mathrm{HH}}-2p_{\mathrm{HH}}-4\beta t p_{\mathrm{HH}}+t)+2\mu^2 p_{\mathrm{HH}}-2p_{\mathrm{HH}}-\mu^2+1}{(\mu-1)(2p_{\mathrm{HH}}-1)}$. We can verify that $\frac{\partial^2 W^A}{\partial\beta\partial a} = (\mu-1)\bar{\theta}\left(2p_{\mathrm{HH}}-1\right) > 0$. Thus there is a only threshold and when $a < \bar{a}_k$, we have $\frac{\partial W^A}{\partial \beta} < 0$ when $\bar{\theta}$ is given.

Next, it can found that $\frac{\partial W^A}{\partial \bar{\theta}} = 2\beta p_{\mathrm{HH}}\left(2\bar{\theta}\left((2\beta-1)\mu^2+\beta t+1\right) + (\mu-1)(a-\mu-1)\right) - 2\bar{\theta}\left(\beta\mu^2+\beta+(\beta-1)t+t\right) + \beta\left(-a\mu+a+\mu^2-1\right) - 2K$, let it equal to 0, we can obtain the threshold

$$
\bar{\theta}_{max} = \frac{\beta(\mu-1)(a-\mu-1) + 2\beta\left(-a\mu+a+\mu^2-1\right)p_{\mathrm{HH}} + 2K - t}{4\beta p_{\mathrm{HH}}\left((2\beta-1)\mu^2+\beta t+1\right) - 2\left(\beta\mu^2+\beta+(\beta-1)t+t\right)}
$$

and $\frac{\partial^2 W^A}{\partial \theta^2} = 4\beta p_{\mathrm{HH}}\left((2\beta-1)\mu^2+\beta t+1\right) - 2\left(\beta\mu^2+\beta+(\beta-1)t+t\right) < 0$. Thus, we find the unique threshold. It is easy to check that we can also use a $\bar{a}_l$ as a threshold in this situation:

$\frac{\partial^2 W^A}{\partial\bar{\theta}\partial a} = \beta(\mu-1)\left(2p_{\text{HH}}-1\right) > 0$ and

$$\bar{a}_l = \frac{2\bar{\theta}\left(\beta\mu^2+\beta-2\beta p_{\text{HH}}\left((2\beta-1)\mu^2+\beta t+1\right)+\beta t\right)-\beta\mu^2}{\beta(\mu-1)\left(2p_{\text{HH}}-1\right)} + \frac{\beta+2\beta\left(\mu^2-1\right)p_{\text{HH}}+2K}{\beta(\mu-1)\left(2p_{\text{HH}}-1\right)}.$$

Together with the results of Proposition 1, we can know that as β increases, $\bar{\theta}$ will increase. When $a < \bar{a} = \min(\bar{a}_k, \bar{a}_l)$, the total welfare will decrease. Thus, when the market potential is lower, the yield prediction feature may hurt farmers' welfare.

Next, we analyze the effect of the adoption cost K on welfare W^A. Taking the first-order derivative of W^A with respect to K yields:

$$\frac{\partial W^A}{\partial K} = \frac{-4\beta p_{\text{HH}}\left(2t\left(a(\beta+1)(\mu-1)-(\beta+1)\left(\mu^2-1\right)+2K\right)-\left(\mu^2-1\right)\left(\beta\mu^2+1\right)\right)+M_1}{\beta\left(-p_{\text{HH}}\left((4\beta-2)\mu^2+4\beta t+2\right)+\mu^2+2t+1\right)^2},$$

where $M_1 = 4\beta(\mu-1)p_{\text{HH}}^2\left(4\beta t(a-\mu-1)-(\mu+1)\left((2\beta-1)\mu^2+1\right)\right)+4\beta(\mu-1)t(a-\mu-1)-\beta\mu^4+\beta+8Kt$. To determine the sign of this derivative, we evaluate its monotonicity with respect to the market potential a. We define a threshold $\bar{a}'$ such that $\frac{\partial W^A}{\partial K}\big|_{a=\bar{a}'} = 0$, which is explicitly given by:

$$\bar{a}' = \frac{-4\beta p_{\text{HH}}\left(\left(\mu^2-1\right)\left(\beta\mu^2+1\right)-4Kt+2(\beta+1)\left(\mu^2-1\right)t\right)+M_2}{4\beta(\mu-1)t\left(2p_{\text{HH}}-1\right)\left(2\beta p_{\text{HH}}-1\right)},$$

where $M_2 = 4\beta\left(\mu^2-1\right)p_{\text{HH}}^2\left((2\beta-1)\mu^2+4\beta t+1\right)-8Kt+\beta\left(\mu^2-1\right)\left(\mu^2+4t+1\right)$. Taking the cross-partial derivative of W^A with respect to K and a, we obtain:

$$\frac{\partial^2 W^A}{\partial K\partial a} = \frac{4(\mu-1)t\left(2p_{\text{HH}}-1\right)\left(2\beta p_{\text{HH}}-1\right)}{\left(-p_{\text{HH}}\left((4\beta-2)\mu^2+4\beta t+2\right)+\mu^2+2t+1\right)^2}.$$

Based on our fundamental parameter settings, we have $t > 0$, $\mu < 1$, and $p_{\text{HH}} < 1/2$. Consequently, we have $\mu-1 < 0$ and $2p_{\text{HH}}-1 < 0$. Furthermore, since the prediction accuracy satisfies $0 < \beta < 1$, it strictly follows that $\beta p_{\text{HH}} < 1/2$, which yields $2\beta p_{\text{HH}}-1 < 0$. The product of these three strictly negative terms ensures that the numerator is negative. Since the denominator is squared, we can unambiguously conclude that:

$$\frac{\partial^2 W^A}{\partial K\partial a} < 0.$$

This negative cross-partial derivative indicates that $\frac{\partial W^A}{\partial K}$ is strictly decreasing in a. Consequently, for any market potential below the threshold ($a < \bar{a}'$), we have $\frac{\partial W^A}{\partial K} > 0$. Thus, the adopter welfare W^A is strictly increasing in the adoption cost K when the market size a is relatively small.

Proposition 2 is proved.■

Proof of Proposition 3. We evaluate the marginal impact of the prediction accuracy β on total welfare W at the threshold where agtech adoption just begins. Let $\bar{\beta} = \frac{4K}{(2a-\mu-1)(\mu-1)(2p_{HH}-1)}$ denote the critical threshold such that no farmers adopt agtech (i.e., $\bar{\theta} = 0$). When β marginally increases above $\bar{\beta}$, farmers located near the middle of the Hotelling line begin to adopt agtech ($\bar{\theta} \to 0^+$). The total derivative of welfare with respect to β is given by:

$$\frac{dW^A}{d\beta} = \frac{\partial W^A}{\partial \bar{\theta}} \frac{\partial \bar{\theta}}{\partial \beta} + \frac{\partial W^A}{\partial \beta}.$$

From the proof of Proposition 2, the partial derivative of W with respect to β for a given $\bar{\theta}$ is:

$$\frac{\partial W^A}{\partial \beta} = \bar{\theta}\Big(2\bar{\theta}p_{\mathrm{HH}}\left((4\beta - 1)\mu^2 + 2\beta t + 1\right) - \bar{\theta}(\mu^2 + t + 1) + (\mu - 1)(a - \mu - 1)(2p_{\mathrm{HH}} - 1)\Big).$$

It is evident that as $\bar{\theta} \to 0^+$, the direct effect vanishes:

$$\lim_{\bar{\theta} \to 0^+} \frac{\partial W^A}{\partial \beta} = 0.$$

Next, we evaluate the partial derivative $\frac{\partial W}{\partial \bar{\theta}}$ at $\bar{\theta} \to 0^+$. Taking the limit yields:

$$\lim_{\bar{\theta} \to 0^+} \frac{\partial W^A}{\partial \bar{\theta}} = -2K - \bar{\beta} + a\bar{\beta} - a\bar{\beta}\mu + \bar{\beta}\mu^2 + 2\bar{\beta}(a - \mu - 1)(\mu - 1)p_{HH}.$$

Substituting $\bar{\beta} = \frac{4K}{(2a-\mu-1)(\mu-1)(2p_{HH}-1)}$ into this expression and simplifying yields:

$$\lim_{\bar{\theta} \to 0^+} \frac{\partial W^A}{\partial \bar{\theta}} = -\frac{2K(1+\mu)}{2a - \mu - 1}.$$

Therefore, the total marginal effect on welfare evaluated at $\beta \to \bar{\beta}^+$ reduces to:

$$\lim_{\beta \to \bar{\beta}^+} \frac{dW^A}{d\beta} = -\frac{2K(1+\mu)}{2a - \mu - 1} \frac{\partial \bar{\theta}}{\partial \beta}.$$

From Proposition 1, we establish that $\frac{\partial \bar{\theta}}{\partial \beta} > 0$. Furthermore, given the fundamental parameter definitions, we have $K > 0$, $\mu > 0$, and $2a - \mu - 1 > 0$. Consequently, the coefficient is strictly negative: $-\frac{2K(1+\mu)}{2a-\mu-1} < 0$. Thus, $\lim_{\beta \to \bar{\beta}^+} \frac{dW^A}{d\beta} < 0$, which proves that total welfare strictly decreases when a small mass of farmers begins to adopt agtech. Since when $\bar{\theta} = 0$, we have $W^A = W^N$. Proposition 3 is proved. ■

Proof of Proposition 4. Next, we assume that using the agtech, each farmer's expertise-related production cost will be reduced by a factor $(1 - \omega)$, where $0 \le \omega \le 1$, regardless of which crop they grow. As such, with the service, a farmer at location θ will incur a cost $c_1^A(\theta) = \omega t(0.5 + \theta) + C$ if growing crop 1, and a cost $c_2^A(\theta) = \omega t(0.5 - \theta) + C$ if growing crop 2. For brevity, we define $\tau = 1 - \omega$ as the level of cost reduction achieved by the service, where a larger τ signifies a greater magnitude of cost reduction.

Then we can obtain the expected profits of the farmer at location θ receiving the signal:

$$\mathbb{E}(\pi_1 | s_1, s_2) = a\mathbb{E}(z_1 | s_1, s_2) - \mathbb{E}(z_1^2 | s_1, s_2)q_1(H, H) - K - \left(\theta + \frac{1}{2}\right) t\omega - C,$$

$$\mathbb{E}(\pi_2 | s_1, s_2) = a\mathbb{E}(z_2 | s_1, s_2) - \mathbb{E}(z_2^2 | s_1, s_2)q_2(H, H) - K - \left(-\theta + \frac{1}{2}\right) t\omega - C.$$

Specifically, the expected profits of the farmer at location θ using agtech in the case with different agtech signals can be shown as

$$
\begin{aligned}
\mathbb{E}(\pi_1\,|H,H\,) &= \frac{\beta p_{\mathrm{HH}}\left(-2a((\beta-1)\mu+1)+2(\beta-1)\mu^2q_1(H,H)+2q_1(H,H)+\beta(2\theta+1)t\omega\right)}{2\beta-2\beta^2p_{\mathrm{HH}}-2}\\
&+\frac{2\beta^2p_{\mathrm{HH}}K+(\beta-1)\left(a\mu+a-2K+\mu^2(-q_1(H,H))-q_1(H,H)-2\theta t\omega-t\omega\right)}{2\beta-2\beta^2p_{\mathrm{HH}}-2}-C\\
&=\frac{\beta p_{\mathrm{HH}}\left(-2a((\beta-1)\mu+1)+[2(\beta-1)\mu^2+2]q_1(H,H)+\beta(2\theta+1)t(1-\tau)\right)}{2\beta-2\beta^2p_{\mathrm{HH}}-2}\\
&+\frac{2\beta^2p_{\mathrm{HH}}K+(\beta-1)\left(a\mu+a-2K+(\mu^2-1)(-q_1(H,H))-2(\theta+1)t(1-\tau)\right)}{2\beta-2\beta^2p_{\mathrm{HH}}-2}-C,
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}(\pi_2\,|H,H\,) &= \frac{\beta p_{\mathrm{HH}}\left(2a((\beta-1)\mu+1)-\beta(2K+(1-2\theta)t\omega)-2q_2(H,H)\left((\beta-1)\mu^2+1\right)\right)}{-2\beta+2\beta^2p_{\mathrm{HH}}+2}\\
&-\frac{(\beta-1)\left(a\mu+a-2K+\mu^2(-q_2(H,H))-q_2(H,H)+2\theta t\omega-t\omega\right)}{-2\beta+2\beta^2p_{\mathrm{HH}}+2}-C\\
&=\frac{\beta p_{\mathrm{HH}}\left(2a((\beta-1)\mu+1)-\beta(2K+(1-2\theta)t(1-\tau))-2q_2(H,H)\left((\beta-1)\mu^2+1\right)\right)}{-2\beta+2\beta^2p_{\mathrm{HH}}+2}\\
&-\frac{(\beta-1)\left(a\mu+a-2K+\mu^2(-q_{2(H,H)})-q_2(H,H)+(2\theta-1)t(1-\tau)\right)}{-2\beta+2\beta^2p_{\mathrm{HH}}+2}-C,
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}(\pi_1\,|H,L\,) &= \frac{p_{\mathrm{HH}}\left(4a((\beta-1)\mu+1)\right)-2a+2K+2q_1(H,L)+(2\theta+1)t\omega}{4\beta p_{\mathrm{HH}}-2}\\
&-\frac{2p_{\mathrm{HH}}\left(\left(2\beta K+2(\beta-1)\mu^2q_1(H,L)+2q_1(H,L)+\beta(2\theta+1)t\omega\right)\right)}{4\beta p_{\mathrm{HH}}-2}-C\\
&=\frac{p_{\mathrm{HH}}\left(4a((\beta-1)\mu+1)\right)-2a+2K+2q_1(H,L)+(2\theta+1)t(1-\tau)}{4\beta p_{\mathrm{HH}}-2}\\
&-\frac{2p_{\mathrm{HH}}\left(\left(2\beta K+2(\beta-1)\mu^2q_1(H,L)+2q_1(H,L)+\beta(2\theta+1)t(1-\tau)\right)\right)}{4\beta p_{\mathrm{HH}}-2}-C,
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}(\pi_2\,|L,H\,) &= \frac{p_{\mathrm{HH}}\left(4a((\beta-1)\mu+1)\right)-2a+2K+2q_2(L,H)-2\theta t\omega+t\omega}{4\beta p_{\mathrm{HH}}-2}\\
&-\frac{2p_{\mathrm{HH}}\left(2\left(2\beta K+2(\beta-1)\mu^2q_2(L,H)+2q_2(L,H)+\beta(1-2\theta)t\omega\right)\right)}{4\beta p_{\mathrm{HH}}-2}-C\\
&=\frac{p_{\mathrm{HH}}\left(4a((\beta-1)\mu+1)\right)-2a+2K+2q_2(L,H)-(2\theta-1)t(1-\tau)}{4\beta p_{\mathrm{HH}}-2}\\
&-\frac{2p_{\mathrm{HH}}\left(2\left(2\beta K+2(\beta-1)\mu^2q_2(L,H)+2q_2(L,H)+\beta(1-2\theta)t(1-\tau)\right)\right)}{4\beta p_{\mathrm{HH}}-2}-C,
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}(\pi_2\,|H,L\,) &= a\mu-K+\mu^2(-q_2(H,L))+\theta t\omega-\frac{t\omega}{2}-C\\
&=a\mu-K+\mu^2(-q_2(H,L))+\theta t(1-\tau)-\frac{t(1-\tau)}{2}-C,
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}(\pi_1\,|L,H\,) &= a\mu-K+\mu^2(-q_1(H,L))-\left(\theta+\frac{1}{2}\right)t\omega-C\\
&=a\mu-K+\mu^2(-q_1(H,L))-\left(\theta+\frac{1}{2}\right)t(1-\tau)-C,
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}(\pi_1 \,|L, L) &= a\mu - K + \mu^2(-q_1(L, L)) - \left(\theta + \frac{1}{2}\right) t\omega - C \\
&= a\mu - K + \mu^2(-q_1(L, L)) - \left(\theta + \frac{1}{2}\right) t(1 - \tau) - C,
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}(\pi_2 \,|L, L) &= a\mu - K + \mu^2(-q_2(L, L)) + \theta t\omega - \frac{t\omega}{2} - C \\
&= a\mu - K + \mu^2(-q_2(L, L)) + \theta t(1 - \tau) - \frac{t(1 - \tau)}{2} - C.
\end{aligned}
$$

Next, by the backward induction, we try to obtain the threshold of farmers' crop choices:

If a farmer does not use agtech or agtech is not introduced to the market, it is easy to find that he will choose crop 1 if $\theta < 0$. Otherwise, he will choose crop 2.

If a farmer uses agtech, he will plant the crop based on the considering of the signal and his expected profits. Take the situation where the signal is (H, L) as an example.

$\hat{\theta}$ should satisfy $\mathbb{E}(\pi_1 \,|H, L) = \mathbb{E}(\pi_2 \,|H, L)$, then we have

$$
\begin{aligned}
\hat{\theta} &= \min \left\{ \frac{a \left[\mathbb{E}\left(z_1 \,|H, L\right) - \mathbb{E}\left(z_2 \,|H, L\right)\right] - \left[q_1 \mathbb{E}\left(z_1^2 \,|H, L\right) - q_2 \mathbb{E}\left(z_2^2 \,|H, L\right)\right]}{2t\omega}, 0.5 \right\} \\
&= \min \left\{ \frac{a \left[\mathbb{E}\left(z_1 \,|H, L\right) - \mathbb{E}\left(z_2 \,|H, L\right)\right] - \left[q_1 \mathbb{E}\left(z_1^2 \,|H, L\right) - q_2 \mathbb{E}\left(z_2^2 \,|H, L\right)\right]}{2t(1 - \tau)}, 0.5 \right\}.
\end{aligned}
$$

Thus, when a farmer using agtech receives a signal (H, L), if his location $\theta < \hat{\theta}$, he will plant crop 1; otherwise he will plant crop 2.

Since the two crops in the model are completely symmetrical, we can obtain that the threshold in the situation with signal (L, H) is $-\hat{\theta}$.

Finally, when the signals are (L, L) and (H, H), we can easily check that the thresholds are equal to 0.

Next, by comparing the expected incomes of farmers adopting or not adopting agtech, we can obtain the farmers' agtech adoption decisions, which is associated with the threshold $\bar{\theta}$.

If a farmer at location θ adopts the agtech, conditional on realized signal (s_1, s_2), his expected profit is given by

$$
\mathbb{E}(\pi_i | s_1, s_2) = a\mathbb{E}(z_i | s_1, s_2) - q_i(s_1, s_2)\mathbb{E}(z_i^2 | s_1, s_2) - c_i^A(\theta) - K.
$$

When a farmer receives a signal (s_1, s_2), he can select a crop with higher expected profit. Hence, his anti-expected profit is given by

$$
U_A = \sum_{s_1, s_2 \in \{H, L\}} \Pr\left(s_1, s_2\right) \max_{i \in \{1,2\}} \mathbb{E}(\pi_i | s_1, s_2).
$$

If a farmer at location θ does not adopt agtech, he can also estimate the probability of agtech giving four signals $\Pr(s_1, s_2)$, and then estimate his expected yield and market crop quantity under each signal. However, he does not know what the specific signal is, so he cannot modify his planting decision according to the signal. Thus his profit can be expressed as follows.

First, he can estimate his profit planting crop i under four signals:

$$\mathbb{E}(\pi_i^N|s_1, s_2) = a\mathbb{E}(z_i|s_1, s_2) - q_i(s_1, s_2)\mathbb{E}(z_i^2|s_1, s_2) - c_i(\theta).$$

Then, he can estimate his expected profit:

$$\mathbb{E}(\pi_i^N) = \sum_{s_1, s_2 \in \{H, L\}} \Pr(s_1, s_2)\mathbb{E}(\pi_i^N|s_1, s_2).$$

Hence, his anti-expected profit is given by

$$U_N = \max_{i \in \{1,2\}} \mathbb{E}(\pi_i^N).$$

Consider the right side of the Hotelling line as an example, we can assume there is a threshold $\bar{\theta} \in [0, 0.5]$. It is easy to check that the farmers located at the middle of the hotelling line $\theta \in [-\bar{\theta}, \bar{\theta}]$ are more likely to adopt agtech because they have similar but high production costs for the two crops. However, the farmers located at the two ends of the line have a preferred crop which is close to their location. Thus, they will not easily change their decision and have even less motivation to use agtech.

We can realize that there are two situations depends on the relationship between $\hat{\theta}$ and $\bar{\theta}$. When $\bar{\theta} > \hat{\theta}$, some of the farmers adopting agtech will not plant crop according to the signal, for example, he may plant crop 2 when he receives the signal (H, L) because of his lower production cost for crop 2. That is, he only enjoys the cost reduction feature of agtech. In this situation, $q_1(H,H) = q_2(H,H) = q_1(L,L) = q_2(L,L) = \frac{1}{2}$, $q_1(H,L) = q_2(L,H) = \frac{1}{2} + \hat{\theta}$, $q_2(H,L) = q_1(L,H) = \frac{1}{2} - \hat{\theta}$.

Thus, in this situation, for the farmers located near the threshold $\bar{\theta}$, no matter they adopt agtech or not, they will always select the crop close to their location. Taking these farmers located at the right of the Hotelling line as an example. Then his expected income can be represented by

$$\begin{aligned}
U_A = &\Pr(s_1 = H, s_2 = L)\left(a\mathbb{E}(z_2\,|H, L) - \mathbb{E}(z_2^2\,|H, L)q_2(H, L) - \left(\theta + \frac{1}{2}\right)t(1-\tau)\right) \\
&+ \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_2\,|H, H) - \mathbb{E}(z_2^2\,|H, H)q_2(H, H) - \left(\frac{1}{2} - \theta\right)t(1-\tau)\right) \\
&+ \Pr(s_1 = L, s_2 = H)\left(a\mathbb{E}(z_2\,|L, H) - \mathbb{E}(z_2^2\,|L, H)q_2(L, H) - \left(\frac{1}{2} - \theta\right)t(1-\tau)\right) \\
&+ \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_2\,|L, L) - \mathbb{E}(z_2^2\,|L, L)q_2(L, L) - \left(\frac{1}{2} - \theta\right)t(1-\tau)\right) - K - C,
\end{aligned}$$

$$\begin{aligned}
U_N = &\Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_2\,|H, H) - \mathbb{E}(z_2^2\,|H, H)q_2(H, H)\right) \\
&+ \Pr(s_1 = H, s_2 = L)(a\mathbb{E}(z_2\,|H, L) - \mathbb{E}(z_2^2\,|H, L)q_2(H, L)) \\
&+ \Pr(s_1 = L, s_2 = H)(a\mathbb{E}(z_2\,|L, H) - \mathbb{E}(z_2^2\,|L, H)q_2(L, L)) \\
&+ \Pr(s_1 = L, s_2 = L)(a\mathbb{E}(z_2\,|L, L) - \mathbb{E}(z_2^2\,|L, L)q_2(L, L)) - \left(\frac{1}{2} - \theta\right)t - C.
\end{aligned}$$

The farmer located at the threshold has same income when he use agtech or not. Thus, solving $U_A = U_N$, we have the threshold

$$\bar{\theta}^i = \frac{1}{2} - \frac{K}{t\tau}.$$

In addition, since the farmers are select crop by $\hat{\theta}$, by solving

$$\frac{2p_{\mathrm{HH}}\left(-2a(\mu-1)+\mu^2((2-4\beta)\theta+1)-2\theta-1\right)+2a(\mu-1)+(2\theta-1)\mu^2+2\theta+1}{4t\omega\left(2\beta p_{\mathrm{HH}}-1\right)} = \theta,$$

we can obtain

$$\begin{aligned}\hat{\theta} &= -\frac{(\mu-1)(2a-\mu-1)\left(2p_{\mathrm{HH}}-1\right)}{p_{\mathrm{HH}}\left((8\beta-4)\mu^2+8\beta t\omega+4\right)-2\left(\mu^2+2t\omega+1\right)} \\ &= -\frac{(\mu-1)(2a-\mu-1)\left(2p_{\mathrm{HH}}-1\right)}{p_{\mathrm{HH}}\left((8\beta-4)\mu^2+8\beta t(1-\tau)+4\right)-2\left(\mu^2+2t(1-\tau)+1\right)}.\end{aligned}$$

On the other hand, when $\bar{\theta} < \hat{\theta}$, all the farmers adopting agtech will all choose a crop according to the signal. In this situation, the quantities of crops in the market is determined by the threshold $\bar{\theta}$, i.e., $q_1(H,L) = q_2(L,H) = \bar{\theta} + \frac{1}{2}$; $q_2(H,L) = q_1(L,H) = \frac{1}{2} - \bar{\theta}$; $q_1(H,H) = q_2(H,H) = q_1(L,L) = q_2(L,L) = \frac{1}{2}$.

Thus, taking the farmers located at the right of the Hotelling line as an example, if the farmers adopt agtech, then he will select crop 1 when he receives a signal (H,L). Otherwise, he will plant crop 2. Thus, his income can be represented by

$$\begin{aligned}U_A = &\Pr(s_1=H,s_2=L)\left(a\mathbb{E}(z_1\,|H,L)-\mathbb{E}(z_1^2\,|H,L)q_1(H,L)-\left(\theta+\frac{1}{2}\right)t(1-\tau)\right)\\ &+\Pr(s_1=H,s_2=H)\left(a\mathbb{E}(z_2\,|H,H)-\mathbb{E}(z_2^2\,|H,H)q_2(H,H)-\left(\frac{1}{2}-\theta\right)t(1-\tau)\right)\\ &+\Pr(s_1=L,s_2=H)\left(a\mathbb{E}(z_2\,|L,H)-\mathbb{E}(z_2^2\,|L,H)q_2(L,H)-\left(\frac{1}{2}-\theta\right)t(1-\tau)\right)\\ &+\Pr(s_1=L,s_2=L)\left(a\mathbb{E}(z_2\,|L,L)-\mathbb{E}(z_2^2\,|L,L)q_2(L,L)-\left(\frac{1}{2}-\theta\right)t(1-\tau)\right)-K-C,\end{aligned}$$

$$\begin{aligned}U_N = &\Pr(s_1=H,s_2=H)(a\mathbb{E}(z_2\,|H,H)-\mathbb{E}(z_2^2\,|H,H)q_2(H,H))\\ &+\Pr(s_1=H,s_2=L)(a\mathbb{E}(z_2\,|H,L)-\mathbb{E}(z_2^2\,|H,L)q_2(H,L))\\ &+\Pr(s_1=L,s_2=H)(a\mathbb{E}(z_2\,|L,H)-\mathbb{E}(z_2^2\,|L,H)q_2(L,L))\\ &+\Pr(s_1=L,s_2=L)(a\mathbb{E}(z_2\,|L,L)-\mathbb{E}(z_2^2\,|L,L)q_2(L,L))-\left(\frac{1}{2}-\theta\right)t-C.\end{aligned}$$

Similarly, solving $U_A = U_N$, we have the threshold

$$\bar{\theta}^{ii} = \frac{2a\beta\mu-2a\beta-2\beta(\mu-1)(2a-\mu-1)p_{\mathrm{HH}}-\beta\mu^2+\beta+4K+2t(1-\tau)-2t}{4\beta p_{\mathrm{HH}}\left((2\beta-1)\mu^2+2\beta t(1-\tau)+1\right)-2\left(\beta\left(\mu^2+1\right)+2t((\beta-1)(1-\tau)+1)\right)}.$$

Solve $\bar{\theta}^{ii} = \hat{\theta}$, we have

$$\bar{K} = \frac{1}{2}t\tau\left(1-\frac{(1-\mu)(2a-\mu-1)\left(1-2p_{\mathrm{HH}}\right)}{\left(\mu^2+2t(1-\tau)+1\right)-p_{\mathrm{HH}}\left(-\left((2-4\beta)\mu^2\right)+4\beta t(1-\tau)+2\right)}\right).$$

We can easily check that $\bar{K}$ is the only threshold between the two situation as discussed above.

Thus, when $K \leq \bar{K}$, the threshold that farmers begin to use agtech is $\bar{\theta}^{i}$. Otherwise, the threshold is $\bar{\theta}^{ii}$.

In addition, $\frac{\partial \bar{K}}{\partial a} = \frac{(1-\mu)t\tau(2p_{\mathrm{HH}}-1)}{-2p_{\mathrm{HH}}((2\beta-1)\mu^2+2\beta t(1-\tau)+1)+\mu^2+2t(1-\tau)+1}$. Since $0 < p_{HH} < \frac{1}{2}$, we have $-2p_{\mathrm{HH}}\left((2\beta-1)\mu^2+2\beta t(1-\tau)+1\right)+\mu^2+2t(1-\tau)+1 > 0$ and $(1-\mu)t\tau\left(2p_{\mathrm{HH}}-1\right) < 0$. Thus, $\bar{K}$ and a are negatively correlated. Then we can also use a to characterize the two situations.

Similarly, we can obtain the threshold in the left of the Hotelling line.

The proposition is proved.■

Proof of Proposition 5. For Proposition 5(i), it is easy to check that

$$\frac{\partial \hat{\theta}}{\partial \beta} = \frac{2(\mu-1)(2a-\mu-1)p_{\mathrm{HH}}\left(2p_{\mathrm{HH}}-1\right)\left(\mu^2+t\omega\right)}{\left(-2p_{\mathrm{HH}}\left((2\beta-1)\mu^2+2\beta t\omega+1\right)+\mu^2+2t\omega+1\right)^2}.$$

We can notice that the denominator is positive. In addition, to ensure that the clear prices of the two crops for the farmers are positive, we have to let $2a-\mu-1 \geq 0$. Then, we can prove that the numerator is also positive, which means $\frac{\partial \hat{\theta}}{\partial \beta} > 0$ is always true. When $K > \bar{K}$, $\hat{\theta}$ is meaningless because the crop selection decision is determined by $\bar{K}$. So we does not consider the threshold in this situation.

Next, consider the thresholds determining farmers' agtech adoption decision. $\bar{\theta}^{i}$ is independent of β. However, it should be noticed that $\frac{\partial \bar{\theta}^{ii}}{\partial \beta}$ is quite difficult to verify directly. We focus on the farmers located on the right side of the Hotelling line as an example (Since farmers are symmetrically distributed on the Hotelling line, the results can be extended to the global). Consider the farmer located to the right of $\bar{\theta}^{ii}$ and infinitely close to $\bar{\theta}^{ii}$ ($\theta \rightarrow \bar{\theta}^{ii+}$), which means his income without agtech is really close to the income with agtech, i.e., $\mathbb{E}\left(\pi_{\theta\rightarrow\bar{\theta}^{ii+}}\right)_A = \mathbb{E}\left(\pi_{\theta\rightarrow\bar{\theta}^{ii+}}\right)_N$. Notice that his income with agtech when $K > \bar{K}$ is

$$\mathbb{E}\left(\pi_\theta\right)_A = \frac{1}{4}\begin{pmatrix} 2a(\beta(-\mu)+\beta+\mu+1)-4\beta\theta+\beta\mu^2-\beta-4K-\mu^2+4\theta t\omega-2t\omega-1 \\ 2\beta p_{\mathrm{HH}}\left(2a(\mu-1)-\mu^2+4\theta\left((\beta-1)\mu^2+\beta t\omega+1\right)+1\right)-4\beta\theta t\omega \end{pmatrix} - C.$$

His income without agtech when $K > \bar{K}$ is

$$\mathbb{E}\left(\pi_\theta\right)_N = \frac{1}{4}\left(2a(\mu+1)+2\beta\theta\mu^2-2\beta\theta-4\beta\theta\left(\mu^2-1\right)p_{\mathrm{HH}}-\mu^2+4\theta t-2t-1\right) - C.$$

It should be noticed that $\frac{\partial[\mathbb{E}(\pi_\theta)_A-\mathbb{E}(\pi_\theta)_N]}{\partial\theta} = -\frac{1}{2}\beta\left(\mu^2+1\right)+\beta p_{\mathrm{HH}}\left((2\beta-1)\mu^2+2\beta t\omega+1\right)+t(-\beta\omega+\omega-1) < 0$, which means as θ increases, $\frac{\partial[\mathbb{E}(\pi_\theta)_A-\mathbb{E}(\pi_\theta)_N]}{\partial\theta}$ will decrease. Now consider the effect of parameter β, we find that
$\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial\beta} = \frac{1}{4}\left(2p_{\mathrm{HH}}\left(2a(\mu-1)-\mu^2+\theta\left((8\beta-4)\mu^2+8\beta t\omega+4\right)+1\right)-2a(\mu-1)\right)$
$+\frac{1}{4}\left(-4\theta+\mu^2-4\theta t\omega-1\right)$. In addition, we find $\frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial\beta} = -\frac{1}{2}\theta\left(\mu^2-1\right)\left(2p_{\mathrm{HH}}-1\right) < 0$ is always true. Thus, when $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial\beta} > 0$, i.e., when
$\left(2p_{\mathrm{HH}}\left(2a(\mu-1)-\mu^2+\theta\left((8\beta-4)\mu^2+8\beta t\omega+4\right)+1\right)-2a(\mu-1)\right)+\left(-4\theta+\mu^2-4\theta t\omega-1\right) > 0$, as β increases, the farmer's income with agtech will increase but his income without agtech will decrease, which means $\mathbb{E}\left(\pi_\theta\right)_A > \mathbb{E}\left(\pi_\theta\right)_N$, thus he will prefer to adopt agtech. More farmers intend to use the service and the threshold $\bar{\theta}$ will move right. The above results means that in the situation that $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial\beta} > 0$, $\frac{\partial \bar{\theta}^{ii}}{\partial\beta} > 0$ always holds.

Now we consider the situation $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \beta} < 0$, i.e., . In that case, both $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \beta}$ and $\frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \beta}$ are negative. We can prove that $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \beta} - \frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \beta} > 0$ to verify the result. We have $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \beta} - \frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \beta} = \frac{1}{4}\left(4a(\mu-1)p_{\mathrm{HH}} - 2a(\mu-1) - 2\mu^2 p_{\mathrm{HH}} + 2p_{\mathrm{HH}} + \mu^2 - 1\right)$
$+ \frac{1}{4}\theta\left(2p_{\mathrm{HH}}\left((8\beta-2)\mu^2 + 8\beta t\omega + 2\right) - 2\mu^2 - 4t\omega - 2\right)$. Solve $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \beta} - \frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \beta} = 0$, we have $\theta_K = -\frac{(\mu-1)(2a-\mu-1)(2p_{\mathrm{HH}}-1)}{4p_{\mathrm{HH}}((4\beta-1)\mu^2+4\beta t\omega+1)-2(\mu^2+2t\omega+1)}$. It is easily to verify that in the situation where $2p_{\mathrm{HH}}\left((8\beta-2)\mu^2 + 8\beta t\omega + 2\right) - 2\mu^2 - 4t\omega - 2 > 0$, when $\theta > \theta_K$, we have $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \beta} - \frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \beta} > 0$. Since in that case $\theta_K < 0$ always holds. Thus, in this situation, the effect of β is proved. In the situation where $2p_{\mathrm{HH}}\left((8\beta-2)\mu^2 + 8\beta t\omega + 2\right) - 2\mu^2 - 4t\omega - 2 < 0$, when $\theta < \theta_K$, we have $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \beta} - \frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \beta} > 0$. Since when $K > \bar{K}$, it is easily to check that $\bar{\theta}_{ii} < \hat{\theta} = -\frac{(\mu-1)(2a-\mu-1)(2p_{\mathrm{HH}}-1)}{p_{\mathrm{HH}}((8\beta-4)\mu^2+8\beta t\omega+4)-2(\mu^2+2t\omega+1)}$. It should be noticed that $4p_{\mathrm{HH}}\left((4\beta-1)\mu^2 + 4\beta t\omega + 1\right) - 2\left(\mu^2 + 2t\omega + 1\right) - \left(p_{\mathrm{HH}}\left((8\beta-4)\mu^2 + 8\beta t\omega + 4\right) - 2\left(\mu^2 + 2t\omega + 1\right)\right) = 8\beta p_{\mathrm{HH}}\left(\mu^2 + t\omega\right) > 0$, thus, $\bar{\theta}_{ii} < \hat{\theta} < \theta_K$. Thus, if the farmer located at θ close to $\bar{\theta}_{ii}$, we have $\theta < \theta_K$, which means $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \beta} - \frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \beta} > 0$ always holds. Thus, similarly, though as β increases, $\mathbb{E}\left(\pi_\theta\right)_A$ and $\mathbb{E}\left(\pi_\theta\right)_N$ both decrease, the former decreased less than the latter. Therefore, its better for the farmer located at θ to adopt agtech, which means more farmers will adopt agtech, i.e., $\frac{\partial \bar{\theta}_{ii}}{\partial \beta} > 0$. In summary, we can prove that $\frac{\partial \bar{\theta}^{ii}}{\partial \beta} > 0$ always holds true within the domain of definition when $K > \bar{K}$, the result is proved.

Similarly, consider the relationship between $\bar{\theta}^{ii}$ and ω, for the farmer located at θ close to $\bar{\theta}^{ii}$, $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \omega} = \frac{1}{2}t\left(-2(\beta-1)\theta + 4\beta^2\theta p_{\mathrm{HH}} - 1\right)$ and $\frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \beta} = 0$. Thus, $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \omega} - \frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \omega}$ depends on $\frac{1}{2}t\left(-2(\beta-1)\theta + 4\beta^2\theta p_{\mathrm{HH}} - 1\right)$. Solve $\frac{1}{2}t\left(-2(\beta-1)\theta + 4\beta^2\theta p_{\mathrm{HH}} - 1\right) = 0$, we can obtain $\theta_\omega = \frac{1}{2(-\beta+2\beta^2 p_{\mathrm{HH}}+1)}$. It can be easily verified that $0 < 2\left(-\beta + 2\beta^2 p_{\mathrm{HH}} + 1\right) < 2$, thus, $\frac{1}{2(-\beta+2\beta^2 p_{\mathrm{HH}}+1)} > \frac{1}{2}$, which means $\frac{\partial \mathbb{E}(\pi_\theta)_A}{\partial \omega} - \frac{\partial \mathbb{E}(\pi_\theta)_N}{\partial \omega} < 0$ always holds when $\theta < 1/2$. Therefore, we can prove that $\frac{\partial \bar{\theta}^{ii}}{\partial \omega} < 0$ always holds true within the domain of definition when $K > \bar{K}$, the result is proved.

Consider the relationship between $\hat{\theta}$ and ω, $\frac{\partial \hat{\theta}}{\partial \omega} = \frac{(\mu-1)t(2a-\mu-1)(2p_{\mathrm{HH}}-1)(2\beta p_{\mathrm{HH}}-1)}{(-2p_{\mathrm{HH}}((2\beta-1)\mu^2+2\beta t\omega+1)+\mu^2+2t\omega+1)^2}$, it is easily to verify that $\frac{\partial \hat{\theta}}{\partial \omega} < 0$.

Thus, Proposition 5(ii) is proved.

For Proposition 5(iii), consider the case that $K \leq \bar{K}$, we have $\frac{\partial^2 \hat{\theta}}{\partial \beta \partial \omega} = \frac{2(\mu-1)t(2a-\mu-1)p_{\mathrm{HH}}(2p_{\mathrm{HH}}-1)\left(2p_{\mathrm{HH}}\left((2\beta+1)\mu^2+2\beta t\omega-1\right)-3\mu^2-2t\omega+1\right)}{(-2p_{\mathrm{HH}}((2\beta-1)\mu^2+2\beta t\omega+1)+\mu^2+2t\omega+1)^3}$. It can be proved that $\left(-2p_{\mathrm{HH}}\left((2\beta-1)\mu^2 + 2\beta t\omega + 1\right) + \mu^2 + 2t\omega + 1\right)^3$ is positive. In addition, there is a solution of the numerator, which is $\hat{\omega} = \frac{-2\left((2\beta+1)\mu^2-1\right)p_{\mathrm{HH}}+3\mu^2-1}{2t(2\beta p_{\mathrm{HH}}-1)}$, and $2t\left(2\beta p_{\mathrm{HH}} - 1\right) < 0$. Note that $\tau = 1 - \omega$, thus, proposition 2(ii) is proved.

Proof of Proposition 6. Similarly, when agtech is introduced, the result is more complex. According to Figure 2, the farmers' ex-ante welfare can be represented by

$$W^A = \begin{cases} 2\left[\int_{-0.5}^{-\bar{\theta}^i} U_n(\theta)d\theta + \int_{-\bar{\theta}^i}^{-\hat{\theta}} U_{ac}(\theta)d\theta + \int_{-\hat{\theta}}^{0} U_{acy}(\theta)d\theta\right] & K \leq \bar{K} \\ 2\left[\int_{-0.5}^{-\bar{\theta}^{ii}} U_n(\theta)d\theta + \int_{-\bar{\theta}^{ii}}^{0} U_{acy}(\theta)d\theta\right] & K > \bar{K}, \end{cases}$$

where $U_n(\theta)$, $U_{ac}(\theta)$, and U_{acy} are the expected profits of each nonadopter, adopter for cost reduction only, and adopter for both cost reduction and yield prediction, respectively, as functions of θ. Since the Hotelling line is symmetrical, we can use the left of the line as an example:

$$\begin{aligned}U_n(\theta) &= \Pr(s_1 = H, s_2 = L)\left(a\mathbb{E}(z_1\,|H,L) - \mathbb{E}(z_1^2\,|H,L)q_1(H,L)\right)\\ &+ \Pr(s_1 = L, s_2 = H)\left(a\mathbb{E}(z_1\,|L,H) - \mathbb{E}(z_1^2\,|L,H)q_1(L,H)\right)\\ &+ \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_1\,|H,H) - \frac{\mathbb{E}(z_1^2\,|H,H)}{2}\right)\\ &+ \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_1\,|L,L) - \frac{\mathbb{E}(z_1^2\,|L,L)}{2}\right) - \left(\theta + \frac{1}{2}\right)t - C,\end{aligned}$$

$$\begin{aligned}U_{ac}(\theta) &= \Pr(s_1 = H, s_2 = L)\left(a\mathbb{E}(z_1\,|H,L) - \mathbb{E}(z_1^2\,|H,L)q_1(H,L)\right)\\ &+ \Pr(s_1 = L, s_2 = H)\left(a\mathbb{E}(z_1\,|L,H) - \mathbb{E}(z_1^2\,|L,H)q_1(L,H)\right)\\ &+ \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_1\,|H,H) - \frac{\mathbb{E}(z_1^2\,|H,H)}{2}\right)\\ &+ \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_1\,|L,L) - \frac{\mathbb{E}(z_1^2\,|L,L)}{2}\right) - \left(\theta + \frac{1}{2}\right)t\omega - K - C,\end{aligned}$$

$$\begin{aligned}U_{acy}(\theta) &= \Pr(s_1 = H, s_2 = L)\left(a\mathbb{E}(z_1\,|H,L) - \mathbb{E}(z_1^2\,|H,L)q_1(H,L) - t\omega(\frac{1}{2} + \theta)\right)\\ &+ \Pr(s_1 = L, s_2 = H)\left(a\mathbb{E}(z_1\,|L,H) - \mathbb{E}(z_1^2\,|L,H)q_2(L,H) - t\omega(\frac{1}{2} - \theta)\right)\\ &+ \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_1\,|H,H) - \frac{\mathbb{E}(z_1^2\,|H,H)}{2} - t\omega(\frac{1}{2} + \theta)\right)\\ &+ \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_1\,|L,L) - \frac{\mathbb{E}(z_1^2\,|L,L)}{2} - t\omega(\frac{1}{2} + \theta)\right) - K - C.\end{aligned}$$

Since the two crops are symmetrical, we have $\mathbb{E}(z_1\,|H,L) = \mathbb{E}(z_2\,|L,H)$, $\mathbb{E}(z_1^2\,|H,L) = \mathbb{E}(z_2^2\,|L,H)$, $\Pr(s_1 = H, s_2 = H) + \Pr(s_1 = H, s_2 = L) + \Pr(s_1 = L, s_2 = H) + \Pr(s_1 = L, s_2 = L) = 1$, the above equation can be rearranged as follows (it should be noticed that we omit the details of the equation because the original equation is too complex).

When $K \leq \bar{K}$,

$$\begin{aligned}W^A &= \bar{\theta}^i(t(1-\omega) - 2K) - \left(t(1-\omega)\bar{\theta}^{i2}\right)\\ &+ \Pr(s_1 = H, s_2 = L)\left(2\hat{\theta} + 1\right)\left(a\mathbb{E}(z_1\,|H,L) - \mathbb{E}(z_1^2\,|H,L)\left(\hat{\theta} + \frac{1}{2}\right)\right)\\ &+ \Pr(s_1 = L, s_2 = H)\left(1 - 2\hat{\theta}\right)\left(a\mathbb{E}(z_1\,|L,H) - \mathbb{E}(z_1^2\,|L,H)\left(\frac{1}{2} - \hat{\theta}\right)\right)\\ &+ \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_1\,|H,H) - \frac{\mathbb{E}(z_1^2\,|H,H)}{2}\right)\\ &+ \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_1\,|L,L) - \frac{\mathbb{E}(z_1^2\,|L,L)}{2}\right) - 2\Pr(s_1 = L, s_2 = H)t\omega\hat{\theta}^2 - \frac{t}{4} - C.\end{aligned}$$

When $K > \bar{K}$,

$$\begin{aligned}
W^A &= \Pr(s_1 = H, s_2 = L)\left(2\bar{\theta}^{ii}+1\right)\left(a\mathbb{E}(z_1\,|H,L) - \mathbb{E}(z_1^2\,|H,L)\left(\bar{\theta}^{ii}+\frac{1}{2}\right)\right)\\
&+ \Pr(s_1 = L, s_2 = H)\left(1-2\bar{\theta}^{ii}\right)\left(a\mathbb{E}(z_1\,|L,H) - \mathbb{E}(z_1^2\,|L,H)\left(\frac{1}{2}-\bar{\theta}^{ii}\right)\right)\\
&+ (1-2\Pr(s_1 = L, s_2 = H))t\omega\bar{\theta}^{ii2} - t\bar{\theta}^{ii2} + \bar{\theta}^{ii}(t(1-\omega)-2K)\\
&+ \Pr(s_1 = H, s_2 = H)\left(a\mathbb{E}(z_1\,|H,H) - \frac{\mathbb{E}(z_1^2\,|H,H)}{2}\right)\\
&+ \Pr(s_1 = L, s_2 = L)\left(a\mathbb{E}(z_1\,|L,L) - \frac{\mathbb{E}(z_1^2\,|L,L)}{2}\right) - \frac{t}{4} - C.
\end{aligned}$$

Bring the details of $\mathbb{E}(z_1\,|H,L)$, $\mathbb{E}(z_1^2\,|H,L)$, $\Pr(s_1 = H, s_2 = H)$, $\Pr(s_1 = H, s_2 = L)$, $\Pr(s_1 = L, s_2 = H)$, $\Pr(s_1 = L, s_2 = L)$, as well as $\bar{\theta}$ and $\hat{\theta}$ back to the equation, we can obtain the final welfare (which is omit here).

Considering the direct effect of the features of precision agriculture, given the parameters $\bar{\theta}$ and $\hat{\theta}$, $\frac{\partial W^A_{K<\bar{K}}}{\partial \tau} = -\frac{\partial W^A_{K<\bar{K}}}{\partial \omega} = -t\left(\left(\bar{\theta}^i - 1\right)\bar{\theta}^i + \beta\hat{\theta}^2\left(2\beta p_{\mathrm{HH}} - 1\right)\right)$. Because that $\theta < 1/2$, $p_{HH} < 1/2$, it is easy to check that $\frac{\partial W^A_{K<\bar{K}}}{\partial \tau} > 0$. Similarly, $\frac{\partial W^A_{K>\bar{K}}}{\partial \tau} = -\frac{\partial W^A_{K<\bar{K}}}{\partial \omega} = -t\bar{\theta}^{ii}\left(\bar{\theta}^{ii}\left(-\beta + 2\beta^2 p_{\mathrm{HH}} + 1\right) - 1\right)$ is positive, too. Thus, the cost reduction of precision agriculture always has a positive direct effect on the welfare.

On the other hand, $\frac{\partial W^A_{K<\bar{K}}}{\partial \beta} = \hat{\theta}\left(2p_{\mathrm{HH}}\left((\mu-1)(a-\mu-1) + \hat{\theta}\left((4\beta-1)\mu^2 + 2\beta t\omega + 1\right)\right)\right)$ $-\hat{\theta}\left(\hat{\theta}\left(\mu^2 + t\omega + 1\right) + \mu^2 - 1 + a\mu - a\right)$, by solving the equation $\frac{\partial W^A_{K<\bar{K}}}{\partial \beta} = 0$, we can obtain the threshold

$$\bar{a_1}(\hat{\theta}) = \frac{\mu^2\hat{\theta} + \hat{\theta} - 8\beta\mu^2\hat{\theta}p_{\mathrm{HH}} + 2\mu^2\hat{\theta}p_{\mathrm{HH}} - 2\hat{\theta}p_{\mathrm{HH}} - 4\beta t\omega\hat{\theta}p_{\mathrm{HH}} + t\omega\hat{\theta} + 2\mu^2 p_{\mathrm{HH}} - 2p_{\mathrm{HH}} - \mu^2 + 1}{(\mu-1)\left(2p_{\mathrm{HH}} - 1\right)},$$

and the denominator $(\mu-1)\left(2p_{\mathrm{HH}} - 1\right)$. It should be noticed that $\frac{\partial^2 W^A_{K<\bar{K}}}{\partial\beta\partial a} = (\mu-1)\hat{\theta}\left(2p_{\mathrm{HH}} - 1\right) > 0$. Thus, there is only one threshold in the domain. Similarly, $\frac{\partial W^A_{K>\bar{K}}}{\partial \beta} =$ $\bar{\theta}^{ii}\left(2\bar{\theta}^{ii}p_{\mathrm{HH}}\left((4\beta-1)\mu^2 + 2\beta t\omega + 1\right) - \left(\bar{\theta}^{ii}\left(\mu^2 + t\omega + 1\right)\right) + (\mu-1)(a-\mu-1)\left(2p_{\mathrm{HH}} - 1\right)\right)$, and the threshold

$$\bar{a}_1(\bar{\theta}^{ii}) = \frac{\bar{\theta}^{ii}(\mu^2 + 1 - 8\beta\mu^2 p_{\mathrm{HH}} + 2\mu^2 p_{\mathrm{HH}} - 2p_{\mathrm{HH}} - 4\beta t\omega p_{\mathrm{HH}} + t\omega) + 2\mu^2 p_{\mathrm{HH}} - 2p_{\mathrm{HH}} - \mu^2 + 1}{(\mu-1)\left(2p_{\mathrm{HH}} - 1\right)}.$$

We can verify that $\frac{\partial^2 W^A_{K>\bar{K}}}{\partial\beta\partial a} = (\mu-1)\bar{\theta}^{ii}\left(2p_{\mathrm{HH}} - 1\right) > 0$. Thus there is a only threshold.

In addition, consider the effect of the correlation between the yields of two crops. It is easy to find that $\frac{\partial a_1(\theta)}{\partial p_{HH}} = \frac{2(-1+2\beta)\left(2\mu^2+t\omega\right)\theta}{(-1+\mu)(1-2p_{HH})^2}$. Thus, we can verify the results.

Consider the indirect effects of precision agriculture on the welfare, $\frac{\partial W^A_{K<\bar{K}}}{\partial \hat{\theta}} = \beta(\mu-1)(a-\mu-1)\left(2p_{\mathrm{HH}} - 1\right) + 2\beta\hat{\theta}\left(2p_{\mathrm{HH}}\left((2\beta-1)\mu^2 + \beta t\omega + 1\right) - \mu^2 - t\omega - 1\right)$, $\frac{\partial^2 W^A_{K<\bar{K}}}{\partial\hat{\theta}\partial a} = \beta(\mu-1)\left(2p_{\mathrm{HH}} - 1\right) >$

0. Solving the equation $\frac{\partial W^A_{K<\bar{K}}}{\partial \hat{\theta}} = 0$, we can obtain the unique threshold

$$\bar{a}_2 = \frac{-2p_{\text{HH}}\left(2\hat{\theta}\left((2\beta-1)\mu^2+\beta t\omega+1\right)-\mu^2+1\right)+2\hat{\theta}\left(\mu^2+t\omega+1\right)-\mu^2+1}{(\mu-1)\left(2p_{\text{HH}}-1\right)}.$$

Similarly, $\frac{\partial W^A_{K<\bar{K}}}{\partial \bar{\theta}} = 2t(\omega-1)\bar{\theta}^{ii} - 2K - t\omega + t$, and $\frac{\partial^2 W^A_{K<\bar{K}}}{\partial \bar{\theta}^2} = 2t(\omega-1) < 0$. Thus, the unique threshold exists.

When $K > \bar{K}$, $\frac{\partial W^A_{K>\bar{K}}}{\partial \bar{\theta}} = 2\beta p_{\text{HH}}\left(2\bar{\theta}^{ii}\left((2\beta-1)\mu^2+\beta t\omega+1\right)+(\mu-1)(a-\mu-1)\right)$ $-2\bar{\theta}^{ii}\left(\beta\mu^2+\beta+(\beta-1)t\omega+t\right)+\beta\left(-a\mu+a+\mu^2-1\right)-2K-t\omega+t$, let it equal to 0, we can obtain the threshold

$$\bar{\theta}_{max} = \frac{\beta(\mu-1)(a-\mu-1)+2\beta\left(-a\mu+a+\mu^2-1\right)p_{\text{HH}}+2K+t(\omega-1)}{4\beta p_{\text{HH}}\left((2\beta-1)\mu^2+\beta t\omega+1\right)-2\left(\beta\mu^2+\beta+(\beta-1)t\omega+t\right)}$$

and $\frac{\partial^2 W^A_{K>\bar{K}}}{\partial \bar{\theta}^2} = 4\beta p_{\text{HH}}\left((2\beta-1)\mu^2+\beta t\omega+1\right)-2\left(\beta\mu^2+\beta+(\beta-1)t\omega+t\right) < 0$. Thus, we find the unique threshold. It is easy to check that we can also use a $\bar{a}$ as a threshold in this situation: $\frac{\partial^2 W^A_{K>\bar{K}}}{\partial \bar{\theta}\partial a} = \beta(\mu-1)\left(2p_{\text{HH}}-1\right) > 0$ and

$$\bar{a}_3 = \frac{2\overline{\theta}\left(\beta\mu^2+\beta-2\beta p_{\text{HH}}\left((2\beta-1)\mu^2+\beta t\omega+1\right)+\beta t\omega-t\omega+t\right)-\beta\mu^2}{\beta(\mu-1)\left(2p_{\text{HH}}-1\right)} + \frac{\beta+2\beta\left(\mu^2-1\right)p_{\text{HH}}+2K+t\omega-t}{\beta(\mu-1)\left(2p_{\text{HH}}-1\right)}.$$

Consider the effect of agtech on the welfare. As for the yield prediction, we can know that when $K \leq \bar{K}$, as β increases, $\hat{\theta}$ will also increase, which will further reduce the welfare. In addition, when $a < \bar{a}_1$, the direct effect of β on the welfare is also negative. Thus, when $K < \bar{K}$ and $a < \bar{a}_1$, β has a negative effect on the welfare.

When $K > \bar{K}$, as β increases, $\hat{\theta}$ and $\bar{\theta}$ will both increase. When $a < min(\bar{a}_2, \bar{a}_3)$, the total welfare will decrease. Together with the result obtained before, we can obtain that when $K > \bar{K}$ and $a < min(\bar{a}_1, \bar{a}_2, \bar{a}_3)$, the accuracy of the signal has a negative effect on the welfare. Thus, when the market potential is lower, the yield prediction feature may hurt farmers' welfare. In addition, we can easily check when the correlation between the yields of two crops decreases, the effect of the yield prediction will be amplified.

As for the cost redcution feature, we consider the special case where the prediction is perfectly accurate ($\beta = 1$), $p_{\text{HH}} = 1/4$, and the low-state yield is normalized to $\mu = 0$. Under this setting, for $K > \bar{K}$, the first-order derivative of the total welfare W^A with respect to the cost multiplier ω can be expressed as a quadratic function of the market potential a:

$$\frac{\partial W^A_{K>\bar{K}}}{\partial \omega} = \Lambda_2 a^2 + \Lambda_1 a + \Lambda_0,$$

where the coefficients are given by:

$$\Lambda_2 = \frac{t(2t(\omega-2)+1)}{2(2t(\omega-2)-1)^3},$$
$$\Lambda_1 = -\frac{2t\left(K(4t(\omega-2)+2)+t(2t(\omega-2)+3\omega-5)\right)}{(2t(\omega-2)-1)^3},$$
$$\Lambda_0 = \frac{t\left(64K^2(2t(\omega-2)+1)+64Kt(2t(\omega-2)+3\omega-5)-32t^3\omega^3+\cdots-5\right)}{8(2t(\omega-2)-1)^3}.$$

We first determine the concavity of this quadratic function. Based on the parameter definitions, the cost reduction multiplier satisfies $\omega \in (0,1)$, which yields $\omega - 2 < -1$. Given that $t > 1/2$, it strictly follows that $2t(\omega-2)+1 < 0$ and $2t(\omega-2)-1 < 0$. Consequently, the numerator of Λ_2 is negative and its denominator (a cubed negative number) is also negative, ensuring that:

$$\Lambda_2 > 0.$$

This indicates that the graph of $\frac{\partial W^A}{\partial \omega}$ as a function of a is a parabola opening upwards. Next, we solve for the roots of $\frac{\partial W^A}{\partial \omega} = 0$. Let $\Delta_a = (1-2t(\omega-2))^2\left(16t^2(\omega-2)^2+5\right)$. The two roots are analytically given by:

$$a_{r1} = \frac{8K(2t(\omega-2)+1)+8t^2\omega-16t^2+12t\omega-20t-\sqrt{\Delta_a}}{4t(\omega-2)+2},$$
$$a_{r2} = \frac{8K(2t(\omega-2)+1)+8t^2\omega-16t^2+12t\omega-20t+\sqrt{\Delta_a}}{4t(\omega-2)+2}.$$

Notice that the shared denominator $4t(\omega-2)+2 = 2(2t(\omega-2)+1)$ is strictly negative under our condition $t > 1/2$. Because dividing by a negative denominator reverses the order, the root adding the positive square root $(+\sqrt{\Delta_a})$ evaluates to the smaller value. Thus, we have:

$$a_{r2} < a_{r1}.$$

This is also confirmed by their difference $a_{r1} - a_{r2} = -\frac{\sqrt{\Delta_a}}{2t(\omega-2)+1}$, which is strictly positive. Since the parabola opens upwards ($\Lambda_2 > 0$), the quadratic function evaluates to a strictly positive value for any a strictly outside the interval $[a_{r2}, a_{r1}]$. Therefore, we can verify that under the condition $\frac{1}{2} < t \leq \frac{\sqrt{5}}{4}$ (which ensures $a_{r2} > 0$), for any relatively small market potential satisfying $a < \bar{\bar{a}} \equiv a_{r2}$, we invariably have:

$$\frac{\partial W^A_{K>\bar{K}}}{\partial \omega} > 0.$$

Recall that the cost reduction capability τ is defined as $\tau = 1-\omega$. We have that $\frac{\partial W^A_{K>\bar{K}}}{\partial \tau} < 0$.

Thus, Proposition 6 is proved. ∎

Proof of Proposition 7.

It is easy to check that when $K < \bar{K}$ (in the situation with lower market potential a), the unintended consequence exists. Now we consider the case with larger a, i.e., $K > \bar{K}$. We can notice that when $\bar{\theta} = 0$, which means that $\beta = \bar{\beta} = \frac{4K-2t\tau}{(-1+2a-\mu)(-1+\mu)(-1+2p_{HH})}$, we have all the farmers will not adopt agtech (in the boundary between region II and III in Figure 4a). When β

increases slightly but τ does not change, the farmers located at the middle of the Hotelling line will begin to use agtech. Assume that $\hat{\beta} = \bar{\beta} + \Delta$ and Δ is a very small positive value. Thus, we can use the pair $\left(\tau, \hat{\beta}\right)$ represent the situation where few farmers begin to use agtech, where $\tau < \frac{2K}{t}$ (which ensures $\bar{\beta} > 0$, i.e.,the case where no one use agtech). Substituting $\left(\tau, \hat{\beta}\right)$ back into the welfare, we have the welfare when few farmers begin to use agtech. In this situation, $\frac{\partial W}{\partial \Delta} = \frac{\partial W}{\partial \bar{\theta}} \frac{\partial \bar{\theta}}{\partial \hat{\beta}} \frac{\partial \hat{\beta}}{\partial \Delta} + \frac{\partial W}{\partial \hat{\beta}} \frac{\partial \hat{\beta}}{\partial \Delta} = \frac{\partial W}{\partial \bar{\theta}} \frac{\partial \bar{\theta}}{\partial \hat{\beta}} + \frac{\partial W}{\partial \hat{\beta}}$. It can be easily found that when Δ close to 0, we have $\lim_{\Delta \to 0^+} \bar{\theta} = 0$. Thus, according to the results in Lemma 2, we have $\lim_{\Delta \to 0^+} \frac{\partial W}{\partial \hat{\beta}} = 0$. Thus, $\lim_{\Delta \to 0^+} \frac{\partial W}{\partial \Delta} = \left(-2K + t - \bar{\beta} + a\bar{\beta} - a\bar{\beta}\mu + \bar{\beta}\mu^2 - t(1-\tau) + 2\bar{\beta}\left(-1 + a - \mu\right)\left(-1 + \mu\right) p_{HH}\right) \frac{\partial \bar{\theta}}{\partial \hat{\beta}}$. Bring $\bar{\beta} = \frac{4K - 2t\tau}{(-1+2a-\mu)(-1+\mu)(-1+2p_{HH})}$ back to the original expression, we have $\lim_{\Delta \to 0^+} \frac{\partial W}{\partial \Delta} = -\frac{(1+\mu)(2K-t\tau)}{-1+2a-\mu} \frac{\partial \bar{\theta}}{\partial \hat{\beta}}$. From Proposition 2, we know that $\frac{\partial \bar{\theta}}{\partial \hat{\beta}} > 0$ in the situation where $K > \bar{K}$, thus, when $\frac{(1+\mu)(2K-t\tau)}{-1+2a-\mu} > 0$, we have $\lim_{\Delta \to 0^+} \frac{\partial W}{\partial \Delta} < 0$. Notice that $-1 + 2a - \mu > 0$, thus, when $2K - t\tau > 0$, we have $\lim_{\Delta \to 0^+} \frac{\partial W}{\partial \Delta} < 0$, thus, the proposition is proved.

Similarly, we can define $(\Delta_\tau + \bar{\tau}, \beta)$ as the shift of $(\bar{\tau}, \beta)$ satisfying $\bar{\theta} = 0$. The point $(\Delta_\tau + \bar{\tau}, \beta)$ is on the right of the line $\bar{\theta} = 0$. Set $\hat{\tau} = \Delta_\tau + \bar{\tau}$. We have $\frac{\partial W}{\partial \Delta} = \frac{\partial W}{\partial \bar{\theta}} \frac{\partial \bar{\theta}}{\partial \hat{\tau}} \frac{\partial \hat{\tau}}{\partial \Delta} + \frac{\partial W}{\partial \hat{\tau}} \frac{\partial \hat{\tau}}{\partial \Delta} = \frac{\partial W}{\partial \bar{\theta}} \frac{\partial \bar{\theta}}{\partial \hat{\tau}} + \frac{\partial W}{\partial \hat{\tau}}$. Thus, $\lim_{\Delta \to 0^+} \frac{\partial W}{\partial \Delta_\tau} = -\frac{(1+\mu)(2K-t\tau)}{-1+2a-\mu} \frac{\partial \bar{\theta}}{\partial \hat{\tau}}$, Noticed that $\frac{\partial \bar{\theta}}{\partial \hat{\tau}} > 0$ and $\frac{(1+\mu)(2K-t\tau)}{-1+2a-\mu} > 0$, thus, we have $\lim_{\Delta \to 0^+} \frac{\partial W}{\partial \Delta_\tau} < 0$.

Thus, the proposition is proved.

Proof of Corollary 1. We can easily obtain the welfare when all the farmers are attracted to use agtech, which is $W^F = \frac{1}{4}\left(2a(\beta(-\mu) + \beta + \mu + 1) + 2\beta p_{HH}\left(2a(\mu - 1) + (2\beta - 3)\mu^2 + \beta t\omega + 3\right)\right) + \frac{1}{4}(\beta\mu^2 - 3\beta - 4K - \mu^2 - \beta t\omega - t\omega - 1)$.

Thus, $\frac{\partial W^F}{\partial \beta} = \frac{1}{4}\left(p_{\mathrm{HH}}\left(4a(\mu - 1) + (8\beta - 6)\mu^2 + 4\beta t\omega + 6\right) - 2a(\mu - 1) + \mu^2 - t\omega - 3\right)$. It should be noted that $\frac{\partial^2 W^F}{\partial \beta \partial \omega} = \beta t p_{\mathrm{HH}} - \frac{t}{4}$. When $p_{\mathrm{HH}} < \frac{1}{4\beta}$, we have $\frac{\partial^2 W^F}{\partial \beta \partial \omega} < 0$. Thus, solving $\frac{\partial W^F}{\partial \beta} = 0$, we can obtain the threshold of ω, i.e.,

$$\bar{\omega} = \frac{p_{\mathrm{HH}}\left(-4a(\mu - 1) + (6 - 8\beta)\mu^2 - 6\right) + 2a(\mu - 1) - \mu^2 + 3}{t\left(4\beta p_{\mathrm{HH}} - 1\right)}.$$

Note that $\tau = 1 - \omega$, we have

$$\bar{\tau} = 1 - \frac{p_{\mathrm{HH}}\left(-4a(\mu - 1) + (6 - 8\beta)\mu^2 - 6\right) + 2a(\mu - 1) - \mu^2 + 3}{t\left(4\beta p_{\mathrm{HH}} - 1\right)}.$$

Thus, corollary 1 is proved. ■

A3 Details of Extensions

A3.1 In-Season Monitoring and Contingent Intervention

The extended sequence of events is as follows: (1) Farmers decide whether to adopt the agtech service at a cost of K; (2) The agtech provides a pre-season yield prediction signal. Adopters choose their crop based on this signal, whereas non-adopters rely on their prior experience; (3) During the growing season, agtech provide updated, perfectly accurate signal on the true yield state; (4) Based on the updated state, agtech adopters decide whether to invest an additional cost F for intervention. If the initial true state is low yield (L), the intervention increases the yield from μ to the high yield 1 with probability x. (5) Crops are harvested, markets clear, and farmers realize their profits.

We next prove the propositions in the main paper.

Proof of Proposition 8. To solve this multi-stage game, we employ backward induction. First, we determine the mixed-strategy equilibrium intervention probability ρ given farmers' adoption strategies and pre-season crop selection decisions, and then we derive the pre-season crop selection and agtech adoption thresholds.

Case 1: Low agtech Adoption Cost ($\bar{\theta}^i > \hat{\theta}$)

In equilibrium, upon receiving an updated low-yield signal, adopting farmers employ a mixed strategy: intervening with probability ρ and not intervening with probability $1-\rho$. The indifference condition dictates that the expected profit of intervening exactly equals that of not intervening:

$$((1-x)\mu + x)(a - Q_i) - \omega c_i(\theta) - F - K = \mu(a - Q_i) - \omega c_i(\theta) - K.$$

This condition endogenizes the total market quantity Q_i and the intervention probability ρ. We analyze the four possible initial prediction signals (s_1, s_2) as follows:

(1) Initial signal (H, H) (Probability: $1 - \beta + \beta^2 p_{HH}$)

By symmetry, we focus on crop 2. The conditional probability that the true state is L is $\frac{(-1+\beta)(-1+2\beta p_{HH})}{2-2\beta+2\beta^2 p_{HH}}$. In this state, the expected total market quantity for crop 2 is:

$$Q_2 = \left(\frac{1}{2} - \bar{\theta}^i\right)\mu + \rho\bar{\theta}^i((1-x)\mu + x) + (1-\rho)\bar{\theta}^i\mu.$$

Using the indifference condition, the equilibrium intervention probability and market quantity are:

$$\rho_s^i = -\frac{2F + x(2a-\mu)(-1+\mu)}{2x^2(-1+\mu)^2\bar{\theta}^i}, \quad Q_2 = a + \frac{F}{x(-1+\mu)}.$$

Conversely, the conditional probability of the true state being H is $\frac{1-\beta+2\beta p_{HH}}{2-2\beta+2\beta^2 p_{HH}}$. Farmers do not intervene, yielding $Q_2 = 1/2$. Thus, the expected profits for adopters (Π_A^{HH}) and non-adopters (Π_N^{HH}) under the (H, H) signal are:

$$\begin{aligned}\pi_A^{HH} = {} & \frac{(-1+\beta)(-1+2\beta p_{HH})}{2-2\beta+2\beta^2 p_{HH}}\left[((1-x)\mu + x)\left(a - \left(a + \frac{F}{x(-1+\mu)}\right)\right) - t\omega\left(\frac{1}{2} - \bar{\theta}^i\right) - F - K\right] \\ & + \frac{1-\beta+2\beta p_{HH}}{2-2\beta+2\beta^2 p_{HH}}\left[\left(a - \frac{1}{2}\right) - t\omega\left(\frac{1}{2} - \bar{\theta}^i\right) - K\right] - C,\end{aligned}$$

$$\begin{aligned}\pi_N^{HH} = {} & \frac{(-1+\beta)(-1+2\beta p_{HH})}{2-2\beta+2\beta^2 p_{HH}}\left[\mu\left(a - \left(a + \frac{F}{x(-1+\mu)}\right)\right) - t\left(\frac{1}{2} - \bar{\theta}^i\right)\right] \\ & + \frac{1-\beta+2\beta p_{HH}}{2-2\beta+2\beta^2 p_{HH}}\left[\left(a - \frac{1}{2}\right) - t\left(\frac{1}{2} - \bar{\theta}^i\right)\right] - C.\end{aligned}$$

(2) Initial signal (L, L) (Probability: $\beta^2 p_{HH}$)

The true state is deterministically L. The equilibrium intervention probability remains identical to the (H, H) scenario. The expected profits are:

$$\pi_A^{LL} = ((1-x)\mu + x)\left(a - \left(a + \frac{F}{x(-1+\mu)}\right)\right) - t\omega\left(\frac{1}{2} - \bar{\theta}^i\right) - F - K - C,$$

$$\pi_N^{LL} = \mu\left(a - \left(a + \frac{F}{x(-1+\mu)}\right)\right) - t\left(\frac{1}{2} - \bar{\theta}^i\right) - C.$$

(3) Initial signal (H, L) (Probability: $\frac{1}{2}(\beta - 2\beta^2 p_{HH})$)

Under this heterogeneous signal, the agtech service predicts high yield for crop 1 and low yield for crop 2. Because the agtech service accurately identifies high-yield states without false positives, a low signal for crop 2 guarantees that its true state is deterministically L. However, a high signal for crop 1 could either be a true H or a misclassified L. To endogenize the internal crop selection threshold $\hat{\theta}$ for adopters, we must explicitly formulate the expected profit of planting crop 1 versus crop 2 for a marginal farmer located at $\theta = \hat{\theta}$. If this marginal farmer chooses to plant crop 1, the profit depends on the updated true state revealed in Step 3: if the true state is (H, L) with probability $\frac{1-2p_{HH}}{1-2\beta p_{HH}}$. The market quantity is $Q_1 = \frac{1}{2} + \hat{\theta}$, and the conditional profit is:

$$\pi_1^H(\hat{\theta}) = \left(a - \left(\frac{1}{2} + \hat{\theta}\right)\right) - t\omega\left(\frac{1}{2} + \hat{\theta}\right) - K - C.$$

With conditional probability $1 - \frac{1-2p_{HH}}{1-2\beta p_{HH}}$, the true state is revealed as L. The farmer intervenes. Based on the mixed-strategy equilibrium, the market quantity is $Q_1 = a + \frac{F}{x(-1+\mu)}$, and the conditional profit is:

$$\pi_1^L(\hat{\theta}) = ((1-x)\mu + x)\left(a - \left(a + \frac{F}{x(-1+\mu)}\right)\right) - t\omega\left(\frac{1}{2} + \hat{\theta}\right) - F - K - C.$$

Thus, the expected profit of planting crop 1 is:

$$\mathbb{E}(\pi_1 | H, L) = \frac{1-2p_{HH}}{1-2\beta p_{HH}}\pi_1^H(\hat{\theta}) + \left(1 - \frac{1-2p_{HH}}{1-2\beta p_{HH}}\right)\pi_1^L(\hat{\theta}).$$

If the marginal farmer chooses to plant crop 2, the true state is deterministically L. The farmer engages in the mixed-strategy intervention, leading to a market quantity $Q_2 = a + \frac{F}{x(-1+\mu)}$. The expected profit is:

$$\mathbb{E}(\pi_2 | H, L) = ((1-x)\mu + x)\left(a - \left(a + \frac{F}{x(-1+\mu)}\right)\right) - t\omega\left(\frac{1}{2} - \hat{\theta}\right) - F - K - C.$$

Equating the expected profits, i.e., $\mathbb{E}(\pi_1 | H, L) = \mathbb{E}(\pi_2 | H, L)$, and solving for $\hat{\theta}$ yields the internal threshold:

$$\hat{\theta} = \frac{((-1+2a)x(-1+\mu) + 2F\mu)(-1+2p_{HH})}{2x(-1+\mu)(-1-2t\omega + (2+4t\beta\omega)p_{HH})}.$$

Meanwhile, for adopters located near the outer boundary $\bar{\theta}^i$ (who choose crop 2 despite the prediction), the mixed-strategy intervention probability is determined by the total mass of farmers growing crop 2:

$$\rho_{asc}^{i}=-\frac{2F+x(2a-\mu)(-1+\mu)+2x(-1+\mu)\mu\hat{\theta}}{2x^2(-1+\mu)^2(\bar{\theta}^i-\hat{\theta})},$$

for prediction followers,

$$\rho_{as}^{i}=-\frac{2F+x(2a-\mu)(-1+\mu)-2x(-1+\mu)\mu\hat{\theta}}{2x^2(-1+\mu)^2(\bar{\theta}^i+\hat{\theta})}.$$

The aggregated expected profits for adopters (Π_A^{HL}) and non-adopters (π_N^{HL}) across the entire (H,L) state are:

$$\pi_A^{HL}=((1-x)\mu+x)\left(a-\left(a+\frac{F}{x(-1+\mu)}\right)\right)-t\omega\left(\frac{1}{2}-\bar{\theta}^i\right)-F-K-C,$$

$$\pi_N^{HL}=\mu\left(a-\left(a+\frac{F}{x(-1+\mu)}\right)\right)-t\left(\frac{1}{2}-\bar{\theta}^i\right)-C.$$

(4) Initial signal (L,H) (Probability: $\frac{1}{2}(\beta-2\beta^2p_{HH})$)

Following a similar logic, we derive the expected profits based on the conditional probabilities of the actual states (LH and LL):

$$\begin{aligned}\pi_A^{LH}=&\frac{1-2p_{HH}}{1-2\beta p_{HH}}\left[\left(a-\left(\frac{1}{2}+\hat{\theta}\right)\right)-t\omega\left(\frac{1}{2}-\bar{\theta}^i\right)-K\right]\\&+\left(1-\frac{1-2p_{HH}}{1-2\beta p_{HH}}\right)\left[((1-x)\mu+x)\left(a-\frac{F-ax+ax\mu}{x(-1+\mu)}\right)-t\omega\left(\frac{1}{2}-\bar{\theta}^i\right)-F-K\right]-C,\end{aligned}$$

$$\begin{aligned}\pi_N^{LH}=&\frac{1-2p_{HH}}{1-2\beta p_{HH}}\left[\left(a-\left(\frac{1}{2}+\hat{\theta}\right)\right)-t\left(\frac{1}{2}-\bar{\theta}^i\right)\right]\\&+\left(1-\frac{1-2p_{HH}}{1-2\beta p_{HH}}\right)\left[\mu\left(a-\frac{F-ax+ax\mu}{x(-1+\mu)}\right)-t\left(\frac{1}{2}-\bar{\theta}^i\right)\right]-C.\end{aligned}$$

Aggregating the expected profits across the four signal scenarios based on their prior probabilities, we apply the marginal adopter's indifference condition $\sum P\cdot\Pi_A=\sum P\cdot\Pi_N$. Solving this yields the agtech adoption threshold under the low-cost scenario:

$$\bar{\theta}^i=\frac{1}{2}+\frac{K}{t(\omega-1)}.$$

Case 2: High agtech Adoption Cost ($\bar{\theta}^{ii}<\hat{\theta}$)

When the cost K is relatively large, the crop selection threshold $\hat{\theta}$ under heterogeneous signals falls outside the adoption region and no longer affects the overall equilibrium. We denote the adoption boundary in this regime as $\bar{\theta}^{ii}$, focusing on the right half of the Hotelling line. For signals (H,H) and (L,L), the analysis is perfectly symmetric to the low-cost scenario. The functional forms of the expected profits ($\pi_A^{HH},\pi_N^{HH},\pi_A^{LL},\pi_N^{LL}$) remain identical, with $\bar{\theta}^i$ replaced by $\bar{\theta}^{ii}$. The equilibrium intervention probabilities under heterogeneous signals (H,L) and (L,H) are altered:

$$\rho_{as}^{ii}=-\frac{2F+x(2a-\mu)(-1+\mu)-2x(-1+\mu)\mu\bar{\theta}^{ii}}{4x^2(-1+\mu)^2\bar{\theta}^{ii}}.$$

The expected profits under the (H, L) signal degenerate to:

$$\begin{aligned}\Pi_A^{HL} = & \frac{1-2p_{HH}}{1-2\beta p_{HH}}\left[\left(a-\left(\frac{1}{2}+\bar{\theta}^{ii}\right)\right)-t\omega\left(\frac{1}{2}+\bar{\theta}^{ii}\right)-K\right] \\ & +\left(1-\frac{1-2p_{HH}}{1-2\beta p_{HH}}\right)\left[((1-x)\mu+x)\left(a-\left(a+\frac{F}{x(-1+\mu)}\right)\right)-t\omega\left(\frac{1}{2}+\bar{\theta}^{ii}\right)-F-K\right]-C,\end{aligned}$$

$$\Pi_N^{HL} = \mu\left(a-\mu\left(\frac{1}{2}-\bar{\theta}^{ii}\right)\right)-t\left(\frac{1}{2}-\bar{\theta}^{ii}\right)-C.$$

Similarly, for the (L, H) signal:

$$\begin{aligned}\Pi_A^{LH} = & \frac{1-2p_{HH}}{1-2\beta p_{HH}}\left[\left(a-\left(\frac{1}{2}+\bar{\theta}^{ii}\right)\right)-t\omega\left(\frac{1}{2}-\bar{\theta}^{ii}\right)-K\right] \\ & +\left(1-\frac{1-2p_{HH}}{1-2\beta p_{HH}}\right)\left[((1-x)\mu+x)\left(a-\left(a+\frac{F}{x(-1+\mu)}\right)\right)-t\omega\left(\frac{1}{2}-\bar{\theta}^{ii}\right)-F-K\right]-C,\end{aligned}$$

$$\begin{aligned}\Pi_N^{LH} = & \frac{1-2p_{HH}}{1-2\beta p_{HH}}\left[\left(a-\left(\frac{1}{2}+\bar{\theta}^{ii}\right)\right)-t\left(\frac{1}{2}-\bar{\theta}^{ii}\right)\right] \\ & +\left(1-\frac{1-2p_{HH}}{1-2\beta p_{HH}}\right)\left[\mu\left(a-\left(a+\frac{F}{x(-1+\mu)}\right)\right)-t\left(\frac{1}{2}-\bar{\theta}^{ii}\right)\right]-C.\end{aligned}$$

Finally, by aggregating the expected profits across all four signal realizations and applying the indifference condition, we obtain the closed-form solution for the agtech adoption threshold in the high-adoption-cost regime:

$$\bar{\theta}^{ii} = \frac{x(-1+\mu)\big[4K+\beta(-1+2a-\mu)(-1+\mu)+2t(\omega-1)\big]-T}{2x(-1+\mu)\big[-\beta(1+\mu^2)-2t(1+(\beta-1)\omega)+2\beta(1+\beta(\mu^2+2t\omega))p_{HH}\big]},$$

$$T = 2\beta\big[2F(-1+\beta)\mu+x(-1+\mu)(1-\beta\mu^2+2a(-1+\beta\mu))\big]p_{HH}.$$

Thus, we have:

$$\rho_s^i = \min(\max(-\frac{2F+x(2a-\mu)(-1+\mu)}{2x^2(-1+\mu)^2\bar{\theta}^i}, 0), 1),$$

$$\rho_{as}^i = \min(\max(-\frac{2F+x(2a-\mu)(-1+\mu)-2x(-1+\mu)\mu\hat{\theta}}{2x^2(-1+\mu)^2(\bar{\theta}^i+\hat{\theta})}, 0), 1),$$

$$\rho_{asc}^i = \min(\max(-\frac{2F+x(2a-\mu)(-1+\mu)+2x(-1+\mu)\mu\hat{\theta}}{2x^2(-1+\mu)^2(\bar{\theta}^i-\hat{\theta})}, 0), 1),$$

$$\rho_s^{ii} = \min(\max(-\frac{2F+x(2a-\mu)(-1+\mu)}{2x^2(-1+\mu)^2\ \bar{\theta}^{ii}}, 0), 1),$$

$$\rho_{as}^{ii} = \min(\max(-\frac{2F+x(2a-\mu)(-1+\mu)-2x(-1+\mu)\mu\ \bar{\theta}^{ii}}{4x^2(-1+\mu)^2\ \bar{\theta}^{ii}}, 0), 1).$$

$$\hat{\theta} = \frac{((-1+2a)x(-1+\mu)+2F\mu)(-1+2p_{HH})}{2x(-1+\mu)(-1-2t\omega+(2+4t\beta\omega)p_{HH})},$$

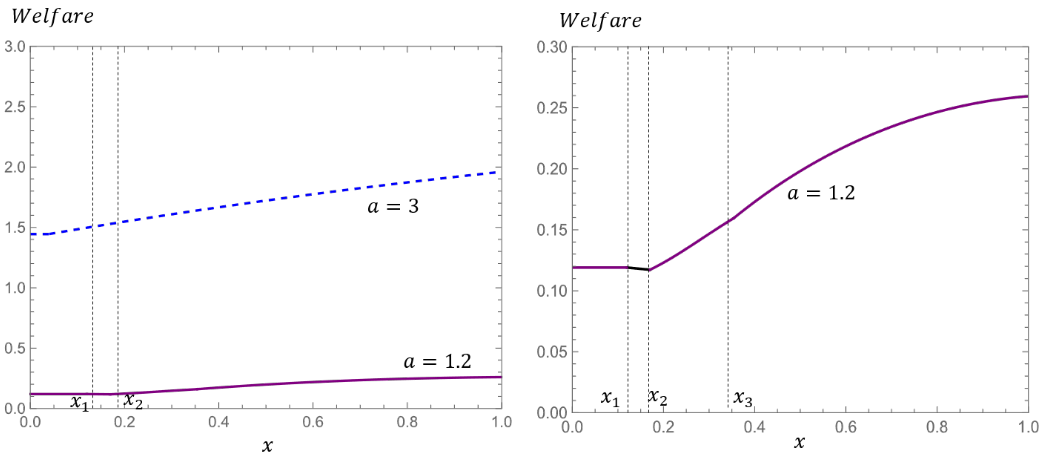
$$\bar{\theta}^i = \frac{1}{2}+\frac{K}{t(\omega-1)},$$

$$\bar{\theta}^{ii} = \frac{x(-1+\mu)\big[4K + \beta(-1+2a-\mu)(-1+\mu) + 2t(\omega-1)\big] - T}{2x(-1+\mu)\big[-\beta(1+\mu^2) - 2t(1+(\beta-1)\omega) + 2\beta(1+\beta(\mu^2+2t\omega))p_{HH}\big]},$$

$$T = 2\beta\big[2F(-1+\beta)\mu + x(-1+\mu)(1-\beta\mu^2+2a(-1+\beta\mu))\big]p_{HH}.$$

It is easily to check that $\rho^i_{as} < \rho^i_s < \rho^i_{asc}$ and $\rho^{ii}_{as} < \rho^{ii}_s$. ■

Proof of Proposition 9. This proposition can be easily proved by the conditions of the mixed-strategy equilibrium. ■



(a) The effect of additional effort on welfare

(b) The details when a is small

Figure A1: The effect of additional effort on welfare

We use a series numerical experiments to examine the effect of the intervention. As can be seen from Figure A1, when the effectiveness of additional effort x is small, no farmers choose to intervene, and therefore x has no impact on farmers' welfare. It is important to note that when x is not too large, it actually has a negative impact on farmers' welfare, which is more significant when a is small ($a = 1.2$), as shown by the black line in Figure A1(b). This also confirms the results of Proposition 9. When x exceeds a certain level, it always has a positive impact on farmers, but when x exceeds x_3, this effect gradually decreases. This is because the effectiveness of additional effort on increasing yield becomes significant, leading to an increase in the quantity of crops in the market and lower prices. The increasing income from further yield-enhancing gradually weakens and eventually disappears. Finally, it can be seen that when the market base size a is large ($a = 3$), farmers begin to intervene earlier, and the impact of x on welfare increases, because the price reduction caused by crop improvement is limited.

Finally, Figure A2 illustrates the impact of yield enhancing on farmers' income inequality. As x increases, the Gini coefficient decreases, indicating that yield-enhancing can mitigate income inequality among farmers in the market. This is because the yield-enhancing feature can further increase the welfare of farmers using the service (who are a disadvantaged group in the original market). Similarly, this effect decreases as x increases.

A3.2 More Than Two Crops

In this section, we demonstrate the robustness of our main results by analyzing an extended setting with three crop options based on a spatial spokes model. For tractability, we assume

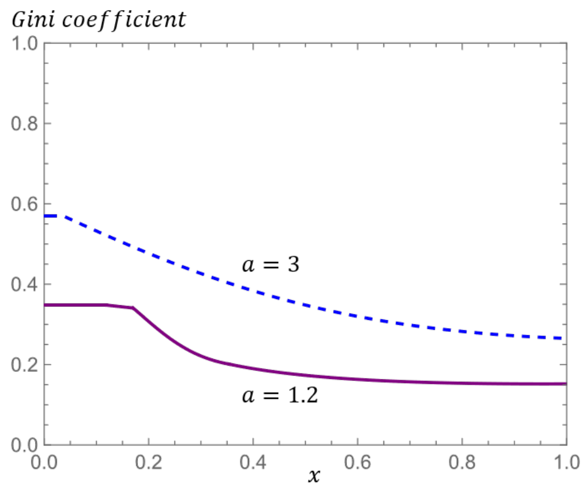


Figure A2: The effect of additional effort on welfare

that the yields across the three crops are independent. Farmers are uniformly distributed on three spokes originating from a central point O, with each of the three endpoints (C_1, C_2, C_3) representing the optimal location for a specific crop. The length of each spoke is $1/2$. As in the base model, farmers located closer to an endpoint incur a lower production cost for growing the corresponding crop. Without loss of generality, we focus our analysis on the farmers located on the spoke OC_1 ($\theta \in [0, 1/2]$). These farmers intuitively prefer crop 1. Under the agtech service, there may exist three indifference points on this spoke similar to our base model:

$\bar{\theta}$, i.e., the boundary determining agtech adoption;

$\hat{\theta}_1$, i.e., the crop selection boundary when the initial agtech signal is (L, H, H);

$\hat{\theta}_2$, i.e., the crop selection boundary when the initial agtech signal is (L, H, L) or (L, L, H).

Under symmetric signals like (H, H, H) or (L, L, L), the crop selection indifference point naturally collapses to the origin O, and under signals like (H, L, L), the indifference point does not lie on the spoke OC_1.

We next prove the propositions in our main paper.

Proof of Proposition 10. Here, we analyze the equilibrium scenario:

Case 1 (Low Agtech Adoption Cost), where $\bar{\theta} > \hat{\theta}_1$ and $\bar{\theta} > \hat{\theta}_2$. In this situation, similar to our main model, a subset of adopters act as "prediction nonfollowers:" even when the agtech predicts a low yield L for crop 1, they persist in planting crop 1 because their cost advantages. We dissect the expected profits under different signal realizations as follows:

(1) Initial Signal is (L, L, L) or (H, H, H), due to the complete symmetry of the signals across all three crops, the crop selection indifference point remains at the origin O. All agtech adopters on spoke OC_1 will continue to grow crop 1. The expected profit is similar to our base model.

(2) Initial Signal is (L, H, L) (or symmetrically (L, L, H)), under this signal, the true state combination could be (L, H, L) or (L, L, L). We establish the expected profit for the marginal farmer located at $\theta = \hat{\theta}_2$. If the farmer insists on planting crop 1, the expected profit is:

$$\mathbb{E}[\pi_1 | LHL] = \mu \left(a - \mu \left(\frac{1}{2} - \hat{\theta}_2 \right) \right) - t\omega \left(\frac{1}{2} - \hat{\theta}_2 \right) - K - C.$$

If the farmer switches to crop 2, the expected profit is a probability-weighted average of the true states, i.e.,

$$\mathbb{E}[\pi_2|LHL] = \frac{\frac{1}{8}\beta^2}{\frac{1}{8}\beta^2 + \frac{1}{8}\beta^2(1-\beta)}((a - (\frac{1}{2} + 2\hat{\theta}_2)) - t\omega(\frac{1}{2} + \theta) - K)$$
$$+ \frac{\frac{1}{8}\beta^2(1-\beta)}{\frac{1}{8}\beta^2 + \frac{1}{8}\beta^2(1-\beta)}(\mu(a - \mu(\frac{1}{2} + 2\hat{\theta}_2)) - t\omega(\frac{1}{2} + \theta) - K) - C.$$

By equating the expected profits of planting crop 1 and crop 2 ($\mathbb{E}[\pi_1|LHL] = \mathbb{E}[\pi_2|LHL]$), we can explicitly solve for the indifference point $\hat{\theta}_2$.

$$\hat{\theta}_2 = \frac{(-1+2a-\mu)(-1+\mu)}{-4+(-8+6\beta)\mu^2 + 4t(-2+\beta)\omega}.$$

(3) Initial Signal is (L, H, H). Under this signal, the true state probabilities are updated via Bayes' rule, too. For the marginal farmer at $\theta = \hat{\theta}_1$, the expected profit of persisting with crop 1 is deterministically low:

$$\mathbb{E}[\pi_1|LHH] = \mu\left(a - \mu\left(\frac{1}{2} - \hat{\theta}_1\right)\right) - t\omega\left(\frac{1}{2} - \hat{\theta}_1\right) - K - C.$$

If the farmer switches to crop 2 (which is symmetric to crop 3), the expected profit relies on the conditional probabilities of the true states:

$$\mathbb{E}[\pi_2|LHH] = \frac{\frac{1}{8}\beta + \frac{1}{8}\beta(1-\beta)}{P_{LHH}}\left[\left(a - \left(\frac{1}{2} + \frac{1}{2}\hat{\theta}_1\right)\right) - t\omega\left(\frac{1}{2} + \hat{\theta}_1\right) - K\right]$$
$$+ \frac{\frac{1}{8}\beta(1-\beta)^2 + \frac{1}{8}\beta(1-\beta)}{P_{LHH}}\left[\mu\left(a - \mu\left(\frac{1}{2} + \frac{1}{2}\hat{\theta}_1\right)\right) - t\omega\left(\frac{1}{2} + \hat{\theta}_1\right) - K\right] - C$$

Setting $\mathbb{E}[\pi_1|LHH] = \mathbb{E}[\pi_2|LHH]$ and solving for $\hat{\theta}_1$, we obtain:

$$\hat{\theta}_1 = \frac{(2a-\mu-1)(\mu-1)}{(-5+3\beta)\mu^2 + 4t(\beta-2)\omega - 1}.$$

By aggregating the ex-ante expected profits across all signal combinations and equating them with the profits of non-adopters, we determine the global agtech adoption threshold on spoke OC_1:

$$\bar{\theta}^i = \frac{1}{2} + \frac{K}{t(\omega-1)}.$$

This specific equilibrium structure (Case 1) holds provided that the adoption cost K is relatively low i.e., $K < K_1$, where the critical threshold K_1 is explicitly given by:

$$K_1 = -\frac{t(\omega-1)\big[-3 - 4a(\mu-1) + 3(\beta-1)\mu^2 - 8t\omega + 4t\beta\omega\big]}{2(-5+3\beta)\mu^2 + 8t(\beta-2)\omega - 2}.$$

Based on our fundamental parameter definitions ($0 < \beta < 1$, $0 < \mu < 1$, $t > 0$, $0 < \omega < 1$, and $2a - \mu - 1 > 0$), we can analytically verify that the threshold hierarchy strictly holds:

$$\bar{\theta} > \hat{\theta}_1 > \hat{\theta}_2.$$

Case 2 (High Agtech Adoption Cost). We now consider the scenario where the agtech adoption cost K is sufficiently high. In this situation, the adoption boundary shrinks such that $\bar{\theta}^{iii} < \hat{\theta}_2 < \hat{\theta}_1$. Consequently, all agtech adopters strictly follow the prediction signal to change their crop choices (i.e., strict prediction followers). To determine the global adoption threshold $\bar{\theta}^{iii}$, we aggregate the expected profits of adopters and non-adopters across all 8 possible initial prediction signals. By spatial symmetry, we focus on the farmers originally located on spoke OC_1:

(1) Signal (L, L, L) (Probability: $\frac{1}{8}\beta^3$):

$$\Pi_A^{LLL} = \mu\left(a - \frac{1}{2}\mu\right) - t\omega\left(\frac{1}{2} - \theta\right) - K - C,$$

$$\Pi_N^{LLL} = \mu\left(a - \frac{1}{2}\mu\right) - t\left(\frac{1}{2} - \theta\right) - C.$$

(2) Signal (H, H, H) (Probability: $\frac{1}{8}(1-\beta)^3 + \frac{3}{8}(1-\beta)^2 + \frac{3}{8}(1-\beta) + \frac{1}{8}$):

The expected profits are weighted by the conditional probabilities of the true underlying states:

$$\Pi_A^{HHH} = P(H|HHH)\left[\left(a - \frac{1}{2}\right) - t\omega\left(\frac{1}{2} - \theta\right) - K\right] + P(L|HHH)\left[\mu\left(a - \frac{1}{2}\mu\right) - t\omega\left(\frac{1}{2} - \theta\right) - K\right] - C,$$

$$\Pi_N^{HHH} = P(H|HHH)\left[\left(a - \frac{1}{2}\right) - t\left(\frac{1}{2} - \theta\right)\right] + P(L|HHH)\left[\mu\left(a - \frac{1}{2}\mu\right) - t\left(\frac{1}{2} - \theta\right)\right] - C,$$

$$P(H|HHH) = \frac{\frac{1}{8} + \frac{2}{8}(1-\beta) + \frac{1}{8}(1-\beta)^2}{\frac{1}{8}(1-\beta)^3 + \frac{3}{8}(1-\beta)^2 + \frac{3}{8}(1-\beta) + \frac{1}{8}},$$

$$P(L|HHH) = \frac{\frac{1}{8}(1-\beta)^3 + \frac{1}{8}(1-\beta) + \frac{2}{8}(1-\beta)^2}{\frac{1}{8}(1-\beta)^3 + \frac{3}{8}(1-\beta)^2 + \frac{3}{8}(1-\beta) + \frac{1}{8}}.$$

Similar Bayesian updating applies to the remaining asymmetric signals.

(3) Symmetric Asymmetric Signals: For signals where the focal crop 1 receives a distinct signal compared to the others, such as (L, H, H) and (H, L, L), adopters will deterministically switch to the crop predicted to have a high yield (e.g., crop 2 or 3). The expected profits are derived similarly by matching the updated conditional probabilities with the corresponding market quantities. For brevity, the full profit expressions for (L, H, L), (H, H, L), (L, L, H), and (H, L, H) follow the exact symmetric logic outlined above.

By equating the ex-ante aggregated expected profit of adopting the agtech service with that of not adopting ($\sum P \cdot \Pi_A = \sum P \cdot \Pi_N$), we explicitly solve for the indifference threshold $\bar{\theta}^{iii}$:

$$\bar{\theta}^{iii} = \frac{16K + \beta(2+\beta)(2a - \mu - 1)(\mu - 1) + t(\omega - 1)\Phi_1}{\beta\big[-2 - 7\beta - \mu^2(10 + 5\beta - 9\beta^2)\big] + 2t\Phi_2}$$

where the parameter bundles Φ_1 and Φ_2 are defined as:

$$\Phi_1 = 8 + 4\beta(\mu-1) - 5\beta^2(\mu-1) + \beta^3(\mu-1),$$

$$\Phi_2 = 4\beta\big[1+\mu(\omega-1)-3\omega\big] + 8(\omega-1) + \beta^3\big[1+\mu(\omega-1)+\omega\big] + 5\beta^2(\mu-1+\omega-\mu\omega).$$

This equilibrium regime strictly holds when $K > K_2$, where the critical threshold K_2 is derived by ensuring $\bar{\theta}^{iii} < \hat{\theta}_2$:

$$K_2 = \frac{3\beta(2a-\mu-1)(\mu-1)\Psi_1 + 2t(\omega-1)\Phi_1\Psi_2 - 4t^2(\beta-2)(\omega-1)\omega\Phi_1}{32\big[-2+(3\beta-4)\mu^2+2t(\beta-2)\omega\big]},$$

where $\Psi_1 = 2-\beta+(2-3\beta+\beta^2)\mu^2$ and $\Psi_2 = 3+2a(\mu-1)-3(\beta-1)\mu^2$.

Case 3: Intermediate agtech Adoption Cost (Selective Prediction Followers)

Finally, we consider the intermediate cost regime where $K_2 \le K \le K_1$. In this scenario, the agtech adoption boundary lies between the two crop selection thresholds: $\hat{\theta}^1 > \bar{\theta}^{ii} > \hat{\theta}^2$. This creates a segmented adoption behavior on spoke OC_1: Farmers located in $[O, \hat{\theta}^2]$ fully follow the signal (strict prediction followers). Farmers located in $[\hat{\theta}^2, \bar{\theta}^{ii}]$ act as selective prediction followers. They follow the agtech signal to switch crops only when the prediction strongly favors alternatives (i.e., signal (L,H,H)). However, if the signal is ambiguous (e.g., (L,H,L)), the expected gain is insufficient to overcome their spatial mismatch cost, and they adhere to their default choice (crop 1). To derive the equilibrium, we must simultaneously solve for two boundaries: the internal selection boundary $\hat{\theta}$ under the ambiguous signal (L,H,L), and the global adoption boundary $\bar{\theta}^{ii}$.

By establishing the crop-switching indifference condition under (L,H,L) for the selective followers, we obtain:

$$\hat{\theta}_2 = \frac{(2a-\mu-1)(\mu-1)}{-4+(6\beta-8)\mu^2+4t(\beta-2)\omega}.$$

Concurrently, we aggregate the expected profits under all 8 signals, substituting the selective switching behavior into the profit functions. Applying the global adoption indifference condition ($\sum P \cdot \Pi_A = \sum P \cdot \Pi_N$) and solving the simultaneous equation system yields the adoption threshold $\bar{\theta}^{ii}$:

$$\bar{\theta}^{ii} = \frac{(\beta-2)\beta(2a-\mu-1)(\mu-1)\big[-2+(3\beta-4)\mu^2\big] - 2t^2\omega(\beta-2)(\omega-1)\Phi_1 - 16K\Omega + t\Lambda}{\Omega\cdot\big[\beta(\beta-2)(-1+(3\beta-5)\mu^2) - 2t\Phi_2\big]},$$

where the structural parameters are simplified as:

$$\Omega = -2+(3\beta-4)\mu^2+2t(\beta-2)\omega,$$

$$\begin{aligned}\Lambda = &-3\beta^4(\mu-1)\mu^2(\omega-1) + 16(1+2\mu^2)(\omega-1) - 2\beta^2(-5+5\mu-16\mu^2+16\mu^3)(\omega-1)\\ &+\beta^3(\mu-1)\big[-2+19\mu^2(\omega-1)-4(a-1)\omega+2\mu\omega\big]\\ &+8\beta\big[1+\mu^2(5-6\omega)+2\mu^3(\omega-1)-2a\omega+\mu(\omega-1+2a\omega)\big].\end{aligned}$$

The proposition is proved. ■

Thus, in the three-crop setting, the impact of yield predictions on farmers' crop choices remains similar to that in our base model, with more nuance arising regarding when farmers choose a recommended crop rather than their default option. Compared to the two-crop case, some farmers may follow the prediction selectively. That is, these farmers switch from their default choices only when the crop nearby is predicted as low yield while *both* alternative crops are predicted as high yield. Otherwise, they maintain their default choice. The intuition is as follows. If exactly one alternative crop is predicted to have high yield, farmers anticipate a large surge in supply of that crop, leading to a substantial price decline, which makes switching unattractive. When both alternative crops are predicted to have high yield, the increased supply would be spread across the two, mitigating the price drop and making it more appealing to switch in response to the signal.

We further assess, through numerical experiments, the welfare implications for farmers when introducing the AgriTech service in the three-crop setting; the results are shown in Figure A3.

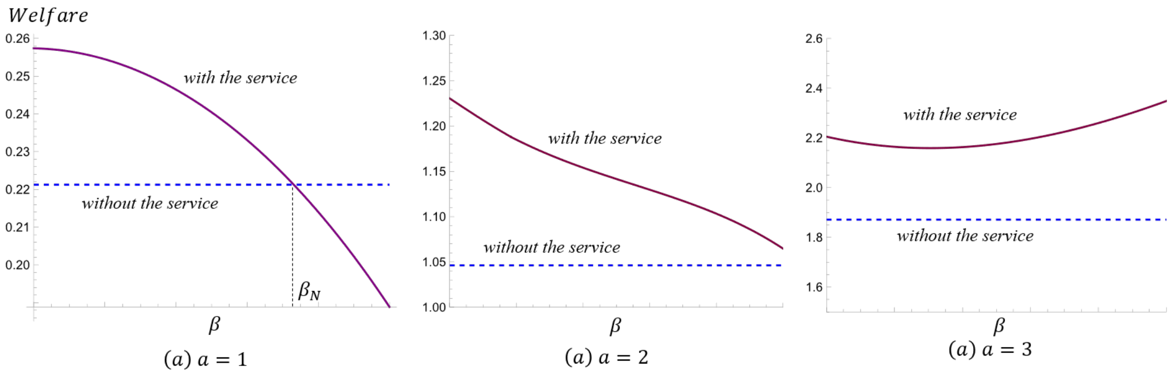


Figure A3: The welfare in three-crop case

As Figure A3 shows, consistent with the main model, higher predictive accuracy of the signal may reduce farmer welfare, and the negative effect is more pronounced when the market potential is small. In addition, when the market is sufficiently small, introducing the service yields lower welfare than the no-AgriTech benchmark, as shown in the Figure A3(a).

In conclusion, our analysis of the three-crop spokes model confirms that the structural properties of the market remain robust. The core insights derived from the baseline two-crop model are fully preserved in a multi-crop spatial framework.

A3.3 False Positive Prediction Error

In our base model, yield predictions serve primarily as warnings of a low-yield state. Accordingly, the information structure is asymmetric: predictions may generate false negatives (failing to warn of a low-yield state with probability $1-\beta$) but involve no false positives (i.e., they never misclassify a high-yield state as low). To further verify the robustness of our core findings, we extend the model to incorporate both false negative and false positive errors. Specifically, for any state $\delta_i \in H, L$, the technology generates a correct signal $s_i = \delta_i$ with probability β, and an incorrect signal $s_i \neq \delta_i$ with probability $1-\beta$. Under this symmetric information structure, an "L" signal no longer perfectly reveals a low-yield state.

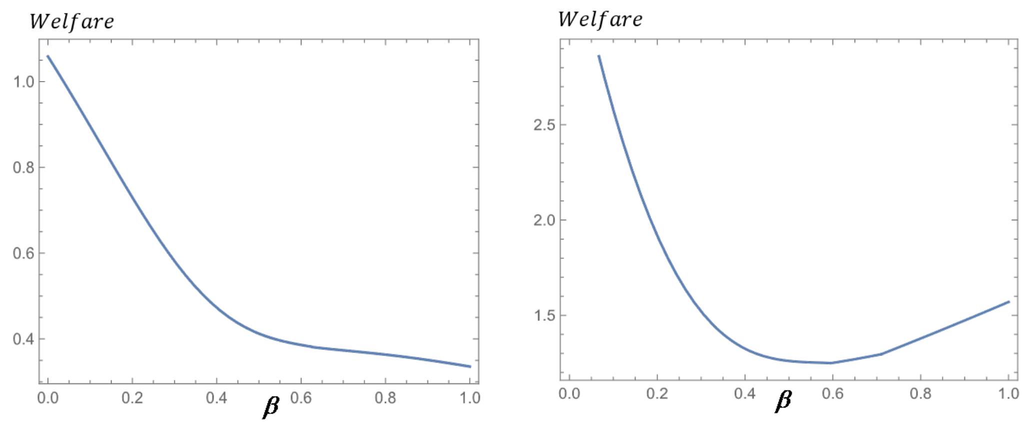
Given the symmetric prediction accuracy β, the unconditional probabilities of realizing the four possible signal profiles (s_1, s_2) are derived as follows:

$$\Pr(s_1 = H, s_2 = H) = 2(1-\beta)\beta(\alpha - p_{HH}) + \beta^2 p_{HH} + (1-\beta)^2(1 - 2\alpha + p_{HH}),$$
$$\Pr(s_1 = L, s_2 = L) = (1-\beta)^2 p_{HH} + 2\beta(1-\beta)(\alpha - p_{HH}) + \beta^2(1 - 2\alpha + p_{HH}),$$
$$\Pr(s_1 = H, s_2 = L) = \beta(1-\beta)(1 - 2\alpha + p_{HH}) + \left(\beta^2 + (1-\beta)^2\right)(\alpha - p_{HH}),$$
$$\Pr(s_1 = L, s_2 = H) = \beta(1-\beta)(1 - 2\alpha + p_{HH}) + (\beta^2 + (1-\beta)^2)(\alpha - p_{HH}).$$

Upon receiving the signal profile (s_1, s_2), farmers update their beliefs using Bayes' rule. Let $\eta_{i(s_1 s_2)} \equiv P(\delta_i = H | s_1, s_2)$ denote the posterior probability that crop i is in a high-yield state. The updated posteriors for crop 1 (and symmetrically for crop 2) under each signal realization are:

$$\eta_{1(H,H)} = \eta_{2(H,H)} = \frac{\beta^2 p_{HH} + \beta(1-\beta)(\alpha - p_{HH})}{\beta^2 p_{HH} + 2\beta(1-\beta)(\alpha - p_{HH}) + (1-\beta)^2(1 - 2\alpha + p_{HH})},$$
$$\eta_{1(L,L)} = \eta_{2(L,L)} = \frac{(1-\beta)^2 p_{HH} + \beta(1-\beta)(\alpha - p_{HH})}{(1-\beta)^2 p_{HH} + 2\beta(1-\beta)(\alpha - p_{HH}) + \beta^2(1 - 2\alpha + p_{HH})},$$
$$\eta_{1(H,L)} = \eta_{2(L,H)} = \frac{\beta(1-\beta)p_{HH} + \beta^2(\alpha - p_{HH})}{\beta(1-\beta)(1 - 2\alpha + p_{HH}) + (\beta^2 + (1-\beta)^2)(\alpha - p_{HH})},$$
$$\eta_{1(L,H)} = \eta_{2(H,L)} = \frac{\beta(1-\beta)p_{HH} + (1-\beta)^2(\alpha - p_{HH})}{\beta(1-\beta)(1 - 2\alpha + p_{HH}) + (\beta^2 + (1-\beta)^2)(\alpha - p_{HH})}.$$

The sequence of events and the equilibrium concept remain identical to the baseline model. Farmers maximize their expected profits based on these updated posterior beliefs. However, due to the bidirectional information errors, the analytical closed-form solutions for the adoption and crop-selection boundaries become highly complex and mathematically intractable. To



(a) Low market potential (a = 1.2) (b) High market potential (a =3)

Figure A4: The welfare under symmetric information structure

demonstrate that our main insights are preserved, we conduct numerical experiments based on this extended setup. The numerical results (illustrated in Figure A4) confirm that our primary findings are highly robust. Specifically, the non-monotonic impact of prediction accuracy persists: as β increases, overall farmer welfare may paradoxically decrease due to intensified market crowding. Furthermore, consistent with the baseline model, this negative welfare effect is mitigated when the market size a is sufficiently large, in which case farmer welfare can increase with the prediction accuracy.

A3.4 Asymmetric Market Potentials

In our base model, we assume symmetric market potentials for both crops. To establish the robustness of our results, we extend the model to an asymmetric setting where crop 1 possesses a larger market potential than crop 2. Specifically, the market potential for crop 1 is $a + n$ ($n > 0$), while the market potential for crop 2 remains a.

By comparing the expected profits of planting crop 1 and crop 2, we can derive the crop selection indifference point for farmers without the agtech service:

$$\theta_N = \frac{n(1+\mu)}{2(1+2t+\mu^2)}.$$

Given this threshold, the baseline total welfare is given by:

$$W^N = \frac{1}{4}\left(-1 - t - \mu^2 + 2a(1+\mu) + n(1+\mu) + \frac{n^2 t(1+\mu)^2}{(1+2t+\mu^2)^2}\right) - C.$$

When the agtech service is introduced, the analysis becomes highly complex. Because the two crops are no longer symmetric, the crop selection thresholds diverge into four distinct points corresponding to the four possible prediction signals: $\hat{\theta}^{HH}$, $\hat{\theta}^{LL}$, $\hat{\theta}^{HL}$, and $\hat{\theta}^{LH}$. Furthermore, the adopters no longer propagates symmetrically from the market center. Instead, adoption originates asymmetrically from a specific point on the right of Hotelling line, resulting in two distinct adoption boundaries, denoted as $\bar{\theta}_1$ (left boundary) and $\bar{\theta}_2$ (right boundary). To maintain tractability, we consider a specific structural case based on the indifference conditions, i.e.,

$$\hat{\theta}^{LH} < \bar{\theta}_1 < \min\{\hat{\theta}^{HH}, \hat{\theta}^{LL}, \theta_N\} \quad \text{and} \quad \max\{\hat{\theta}^{HH}, \hat{\theta}^{LL}, \theta_N\} < \bar{\theta}_2 < \hat{\theta}^{HL}.$$

Under this ordering, when the signals are (H, H) or (L, L), the number of farmers planting each crop is determined by the internal selection boundaries $\hat{\theta}^{HH}$ and $\hat{\theta}^{LL}$. Conversely, when the signals are (H, L) or (L, H), the quantities are constrained by the adoption boundaries $\bar{\theta}_2$ and $\bar{\theta}_1$ (rather than $\hat{\theta}^{LH}$ and $\hat{\theta}^{HL}$). The total quantities of each crop under different signals are explicitly given by:

$$\begin{aligned}
q_1^{HL} &= \frac{1}{2} + \bar{\theta}_2, & q_2^{HL} &= \frac{1}{2} - \bar{\theta}_2, & q_1^{HH} &= \frac{1}{2} + \hat{\theta}^{HH}, & q_2^{HH} &= \frac{1}{2} - \hat{\theta}^{HH}, \\
q_1^{LH} &= \frac{1}{2} + \bar{\theta}_1, & q_2^{LH} &= \frac{1}{2} - \bar{\theta}_1, & q_1^{LL} &= \frac{1}{2} + \hat{\theta}^{LL}, & q_2^{LL} &= \frac{1}{2} - \hat{\theta}^{LL}.
\end{aligned}$$

For any given pair of adoption thresholds $(\bar{\theta}_1, \bar{\theta}_2)$, the crop selection indifference point under signal (H, H) is:

$$\hat{\theta}^{HH} = \frac{n\big[-(\beta-1)(1+\mu) + 2\beta(1+(\beta-1)\mu)p_{HH}\big]}{-2(\beta-1)(1+\mu^2+2t\omega) + 4\beta(1+(\beta-1)\mu^2+t\beta\omega)p_{HH}}.$$

And under signal (L, L), the indifference point is:

$$\hat{\theta}^{LL} = \frac{n\mu}{2(\mu^2 + t\omega)}.$$

For the marginal farmer located at the left adoption boundary $\bar{\theta}_1$, the expected profit of adopting the agtech service is:

$$\begin{aligned}\Pi_A(\bar{\theta}_1) = &\Pr(H,H)\Big[(a+n)\mathbb{E}[z_1|H,H] - q_1^{HH}\mathbb{E}[z_1^2|H,H] - \omega t\Big(\frac{1}{2}+\bar{\theta}_1\Big)\Big] \\ &+ \Pr(H,L)\Big[(a+n)\mathbb{E}[z_1|H,L] - q_1^{HL}\mathbb{E}[z_1^2|H,L] - \omega t\Big(\frac{1}{2}+\bar{\theta}_1\Big)\Big] \\ &+ \Pr(L,H)\Big[a\mathbb{E}[z_2|L,H] - q_2^{LH}\mathbb{E}[z_2^2|L,H] - \omega t\Big(\frac{1}{2}-\bar{\theta}_1\Big)\Big] \\ &+ \Pr(L,L)\Big[(a+n)\mathbb{E}[z_1|L,L] - q_1^{LL}\mathbb{E}[z_1^2|L,L] - \omega t\Big(\frac{1}{2}+\bar{\theta}_1\Big)\Big] - K - C\end{aligned}.$$

If this marginal farmer chooses not to adopt the agtech service, they default to planting crop 1, yielding an expected profit of:

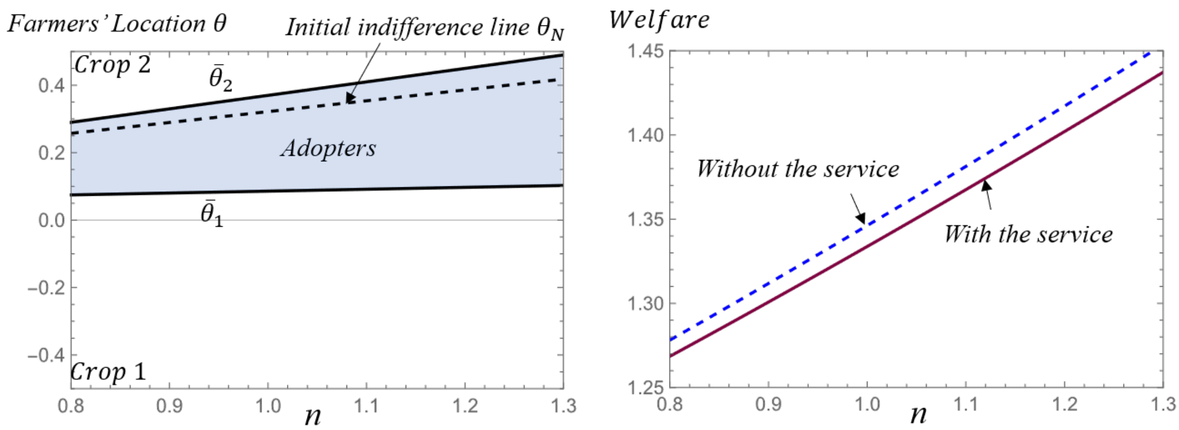
$$\begin{aligned}\Pi_N(\bar{\theta}_1) = &\Pr(H,H)\Big[(a+n)\mathbb{E}[z_1|H,H] - q_1^{HH}\mathbb{E}[z_1^2|H,H]\Big] \\ &+ \Pr(H,L)\Big[(a+n)\mathbb{E}[z_1|H,L] - q_1^{HL}\mathbb{E}[z_1^2|H,L]\Big] \\ &+ \Pr(L,H)\Big[(a+n)\mathbb{E}[z_1|L,H] - q_1^{LH}\mathbb{E}[z_1^2|L,H]\Big] \\ &+ \Pr(L,L)\Big[(a+n)\mathbb{E}[z_1|L,L] - q_1^{LL}\mathbb{E}[z_1^2|L,L]\Big] - t\Big(\frac{1}{2}+\bar{\theta}_1\Big) - C.\end{aligned}$$

A symmetric set of expected profit equations, $\Pi_A(\bar{\theta}_2)$ and $\Pi_N(\bar{\theta}_2)$, can be formulated for the right marginal adopter at $\bar{\theta}_2$. By solving the system of simultaneous equations $\Pi_A(\bar{\theta}_1) = \Pi_N(\bar{\theta}_1)$ and $\Pi_A(\bar{\theta}_2) = \Pi_N(\bar{\theta}_2)$, we can endogenize the asymmetric adoption thresholds $\bar{\theta}_1$ and $\bar{\theta}_2$, which in turn allows us to calculate the total welfare W^A.

Given the complexity of the asymmetric system, we conduct a comprehensive numerical study satisfying the aforementioned threshold conditions to verify the robustness of our results and derive new managerial insights. The details are summarized in Figure A5 and Table 1.

Figure A5(a) illustrates the impact of asymmetric market potentials on farmers' adoption decisions. Naturally, when crop 1 possesses a larger market potential, more farmers are inclined to choose crop 1, shifting the adoption interval $[\bar{\theta}_1, \bar{\theta}_2]$ to the right. Interestingly, we observe that the overall adoption interval expands as the asymmetry parameter n increases. The reason is that as crop 1 becomes significantly more lucrative, farmers located closer to crop 2 face a higher opportunity cost. Consequently, they have a stronger incentive to purchase the yield prediction service to ascertain whether the signal justifies overcoming their mismatch cost to switch to crop 1.

Furthermore, in Table 1, W^A and W^N denote the total welfare with and without the agtech service, respectively. θ_N represents the indifference point for farmers' crop selection in the absence of the service. $\bar{\theta}_1$ and $\bar{\theta}_2$ are the service adoption thresholds, indicating that farmers with location $\theta \in [\bar{\theta}_1, \bar{\theta}_2]$ will adopt the service. The numerical results presented above demonstrate that, even with a large market potential, enhancements in the effectiveness of both features (τ



(a)The impact of asymmetric market potentials on farmers' adoption decision

(b)The impact of asymmetric market potentials on the welfare

Figure A5: The impact of market advantage

Table 1: Performances of the service under asymmetric market potential

(β, τ)	W^A	W^N	$\bar{\theta}_1$	θ_N	$\bar{\theta}_2$
(0.3, 0.1)	0.985314	0.996848	0.0711055	0.238095	0.316277
(0.31,0.1)	0.983903	0.996848	0.0560434	0.238095	0.33389
(0.32,0.1)	0.982575	0.996848	0.0417263	0.238095	0.350646
(0.3,0.11)	0.984895	0.996848	0.0610514	0.238095	0.321257
(0.3,0.12)	0.984528	0.996848	0.0512573	0.238095	0.326107

and β) can still lead to a reduction in total farmer welfare. Furthermore, the welfare with the service may fall below the level observed prior to the technology's introduction. These findings confirm that our baseline model remains robust even in settings with asymmetric crop market potentials.

A4 Impact on Income Inequality When Both Yield Prediction and Cost Reduction Features are considered

Our Hotelling line-based model reflects the reality that specialized farmers (located near the two ends of the Hotelling line) tend to earn a higher income than farmers who do not specialize in either crop (in the middle of the Hotelling line). Our preceding discussion in Section 4.2 has alluded that the introduction of agtech has an impact on income inequality, farmers with different levels of specialization have different incentives to adopt agtech. Now we formally analyze the impact of agtech on farmers' income inequality using the *Gini coefficient*, a commonly used metric for income inequality. The Gini index measures the extent to which the distribution of income among individuals within an economy deviates from a perfectly equal distribution, which is defined based on the Lorenz curve (Tang et al., 2024; Giorgi and Gigliarano, 2017). The Lorenz curve plots the proportion of the total income of the population (y-axis) that is cumulatively earned by the bottom x of the population. The Gini coefficient measures the ratio of the area that lies between the line of equality and the Lorenz curve over the total area under the line of equality.[20] Specifically, in our model, the Lorenz curve can be defined as (taking the situation $K \leq \bar{K}$ as an example)[21]:

$$L(x)_{K\leq\bar{K}} = \begin{cases} \frac{2}{W^A}\int_0^{\frac{x}{2}} U_{acy} d\theta & \text{for } x \in \left[0, 2\hat{\theta}\right], \\ \frac{2}{W^A}\left(\int_0^{\hat{\theta}} U_{acy} d\theta + \int_{\hat{\theta}}^{\frac{x}{2}} U_{ac} d\theta\right) & \text{for } x \in \left[2\hat{\theta}, 2\bar{\theta}^i\right], \\ \frac{2}{W^A}\left(\int_0^{\hat{\theta}} U_{acy} d\theta + \int_{\hat{\theta}}^{\bar{\theta}^i} U_{ac} d\theta + \int_{\bar{\theta}^i}^{\frac{x}{2}} U_n d\theta\right) & \text{for } x \in \left[2\bar{\theta}^i, 1\right]. \end{cases}$$

Then, the Gini coefficient can be represented by:

$$G = 1 - 2\int_0^1 L(x) dx \tag{A1}$$

A Gini coefficient of 0 indicates complete equality, where all income values are identical, whereas a Gini coefficient of 1 (or 100%) signifies extreme inequality among values, depicting a scenario where one individual possesses all the income, leaving none for everyone else.

Example 4. We consider a numerical setting in which the parameters are same as before. We plot the Gini coefficient and the total welfare as functions of yield prediction accuracy β in Figure A6. We have the following observations from panels (a), (b) and (c).

(a) When the market potential is high ($a = 3$), a higher yield prediction can simultaneously enhance the total welfare and reduce income inequality (i.e., result in a lower Gini coefficient), as prediction accuracy β increases. As explained earlier, this is because the nonspecialized farmers in the middle of the Hotelling line benefit the most from agtech, whereas their adoption of agtech can reduce the profits of specialized farmers through intensified competition in the market of recommended crops, thus easing the income inequality.

(b) However, a higher yield prediction does not always alleviate income inequality. When the market potential is low ($a = 1$), a higher β can hurt the total welfare and also exacerbates income inequality. This is because, given a low market potential, a higher β reduces total welfare more prominently than it reduces the absolute difference in farmers' incomes. As a result, the income gap relative to total income increases with β, leading to a rise in the Gini coefficient.

(c) Given the low market potential $a = 1$ but a relatively high cost reduction level $\tau = 0.5$, the Gini coefficient is U-shaped in β, implying that an appropriately high β can alleviate income inequality; however, in this example, a higher β always hurts the total welfare.

The above observations imply that the yield prediction feature can help improve farmer welfare and alleviate income inequality only if the crops have sufficient market potential. Although yield prediction reduces the absolute income difference between specialized and nonspecialized

[20] See more details at `https://databank.worldbank.org/metadataglossary/jobs/series/SI.POV.GINI` accessed September 2, 2024

[21] For the case of $K > \bar{K}$, $L(x)_{K>\bar{K}} = \begin{cases} \frac{2}{W^A}\int_0^{\frac{x}{2}} U_{acy} d\theta & \text{for } x \in \left[0, 2\bar{\theta}^{ii}\right], \\ \frac{2}{W^A}\left(\int_0^{\bar{\theta}^{ii}} U_{acy} d\theta + \int_{\bar{\theta}^{ii}}^{\frac{x}{2}} U_n d\theta\right) & \text{for } x \in [2\bar{\theta}^{ii}, 1]. \end{cases}$

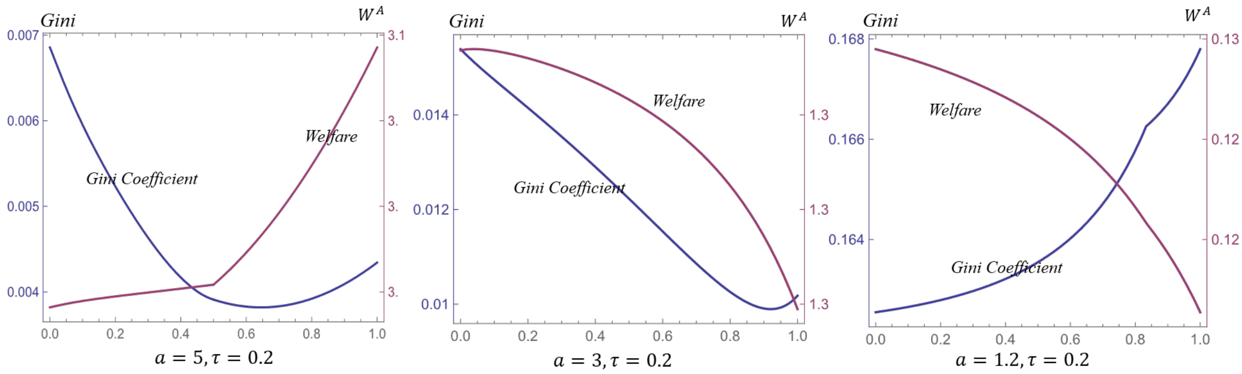


Figure A6: Income inequality implications of agtech

farmers, in the case of low market potential, its welfare-reducing effect may outweigh its impact on the absolute income difference, leading to an increase in the Gini coefficient. In some cases, relieving income inequality and improving welfare can be conflicting objectives when one attempts to improve both metrics through the provision of yield prediction.