Risk and Returns: Economic Drivers of Agrivoltaics Adoption in the U.S. Midwest

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Abstract

Utility-scale solar expansion across U.S. croplands is intensifying food–energy land-use conflicts, particularly in the Midwest. Agrivoltaics (AV), the co-location of photovoltaic systems with agricultural production, offers a potential land-use solution, but its scalability depends on farmer adoption. This study examines how financial incentives, operational requirements, and behavioral factors shape AV adoption decisions using a discrete choice experiment with 177 farmers across 12 Midwestern states (708 choice observations). The experiment evaluates attributes that directly affect farm profitability, risk exposure, and management complexity, including lease payments, income variability, land share under panels, and requirements for new equipment or crop switching. We model adoption as a joint discrete–continuous decision, capturing both the likelihood of adoption and the extent of land allocation to AV. Results show that higher lease payments significantly increase both the probability of adoption and land allocation, highlighting the importance of stable and attractive compensation. In contrast, operational complexity, particularly requirements for new equipment, reduces adoption and generates substantial implicit costs in willingness-to-accept (WTA) estimates. Behavioral characteristics also matter: farmers with higher discount rates are less likely to adopt, whereas risk-tolerant farmers are more willing to participate. Latent class analysis further reveals substantial heterogeneity, distinguishing a majority of cautious “moderate adopters” from a smaller group of “high-intensity adopters” that is more responsive to stable income streams and higher lease compensation. Overall, the findings suggest that financially attractive and operationally simple AV contracts will be critical for scaling adoption while preserving agricultural production.

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Keywords: Agrivoltaics; farmer adoption; discrete choice experiment; willingness to accept (WTA); Lease payments; Joint discrete–continuous model

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1. Introduction

Utility-scale solar energy, which supplies electricity directly to the grid, is currently the fastest-growing sector of new energy generation capacity in the U.S. However, utility-scale photovoltaic (PV) systems are highly land-intensive (Bolinger and Bolinger, 2022; Ong et al., 2013). Croplands, with their high solar energy potential due to flat terrain and abundant sunlight, are particularly attractive for solar energy projects (Adeh et al., 2019). As PV technology costs decline and market and policy incentives rise, solar energy generation is becoming an increasingly profitable use for cropland, even in regions like the Midwest (Maguire et al., 2024). This trend has raised concerns that solar farms may displace food and feed production, prompting some counties to prohibit large-scale solar installations on agricultural land (Susskind et al., 2022).

Agrivoltaics (AV), the co-location of solar panels with crop or livestock production, offers a potential land-use solution by allowing simultaneous food and energy production. While AV has attracted increasing attention from policymakers, developers, and researchers, its success ultimately depends on farmer adoption.[1] This paper addresses a central question: how do farmers evaluate agrivoltaic systems, and what contract terms, technology attributes, and behavioral factors determine their decisions to adopt and allocate land to AV? By focusing on farmer decision-making, the study provides critical evidence on whether AV can scale in real-world agricultural systems.

[1] Throughout the paper, we use the terms "farmers" and "producers" interchangeably to refer to farm operators making land-use decisions. While not all respondents are full landowners, we assume that surveyed operators have sufficient managerial control over operated land to influence or participate in decisions regarding agrivoltaic adoption and land allocation. To account for potential differences in land tenure incentives, the empirical analysis includes the percentage of owned land as a control variable.

A growing body of research shows that farmers are generally receptive to AV when systems provide clear economic and operational benefits, particularly income diversification, compatibility with existing farming practices, and resource efficiencies such as improved water-use and microclimate regulation (e.g., Cuppari et al., 2024; Rumery et al., 2024; Wagner et al., 2024; Lazaridou et al., 2026; Pascaris et al., 2023; 2026). At the same time, however, adoption remains limited. Evidence increasingly points to persistent social, institutional, and economic barriers, including mistrust in developers, uncertainty about long-term land productivity, and concerns about compatibility with farming operations (Pascaris et al., 2020, 2023, 2026; Agir et al., 2023). Beyond these social and institutional constraints, economic considerations remain central: while farmers value AV as a potential source of stable income, financial viability, upfront costs, and contract uncertainty continue to limit uptake (Cuppari et al., 2024; Pascaris et al., 2020, 2023, 2026).

Recent studies further highlight the importance of socio-demographic and place-based factors in shaping the adoption of solar and agrivoltaics systems (Salak et al., 2021; Torma et al., 2023; Zeddies et al., 2025; Lazaridou et al., 2026). For example, Lazaridou et al. (2026) show that farmers' willingness to adopt agrivoltaics is shaped by human and social capital, particularly education, participation in farmer organizations, and familiarity with agro-energy concepts, while high upfront costs, investment risk, and information gaps remain key barriers to uptake. Farmer and public perceptions of AV also vary significantly depending on values related to farmland preservation, landscape identity, and cultural ecosystem services (Caplan et al., 2024). Evidence from Europe suggests that technologies perceived as compatible with existing landscapes and farming systems are more likely to gain acceptance, reinforcing the role of local context in adoption decisions (Salak et al., 2021; Torma et al., 2023; Zeddies et al., 2025).

Despite this expanding literature, important gaps remain. First, most existing studies rely on qualitative interviews or perception-based surveys, which provide limited evidence on how farmers make trade-offs among competing AV attributes in real-world decision contexts (Pascaris et al., 2020, 2021, 2022). Second, little is known about how specific contract terms and system designs, such as lease payments, solar panel footprint, crop-switching requirements, or equipment needs, jointly influence adoption and land allocation decisions. Third, there is limited empirical evidence from the U.S. Midwest, a region that combines high agricultural productivity with rapid growth in utility-scale solar and therefore represents a critical test case for AV deployment.

This study contributes to the literature in three key ways. First, it provides quantitative evidence on farmers' preferences for agrivoltaics in the U.S. Midwest using a discrete choice experiment, allowing us to estimate willingness to adopt under alternative contract and technology configurations. Second, it models adoption as a joint discrete–continuous decision, capturing both the decision to adopt and the extent of land allocation, thereby providing a more complete representation of farmer behavior. Third, it incorporates behavioral factors (e.g., risk and time preferences) alongside farm and demographic characteristics, offering new insights into heterogeneity and the role of uncertainty in AV adoption decisions. To further account for unobserved heterogeneity in farmer preferences, we also employ a latent class framework to identify distinct adoption profiles and examine how different farmer groups respond to financial incentives, income stability, and operational requirements. We provide an economic interpretation of these preferences by translating estimated coefficients into willingness-to-accept (WTA) measures. This allows us to quantify the compensation required for farmers to accept specific agrivoltaic attributes and to assess the relative importance of financial incentives versus operational constraints.

To implement this analysis, we conducted a discrete choice experiment with 177 farmers across 12 Midwestern states, generating 708 choice observations. The experiment varies key attributes of agrivoltaic systems, including lease payments, income variability, land share under panels, and operational requirements such as crop switching and new equipment. This design allows us to quantify the trade-offs farmers make between financial returns, risk, and operational complexity, and to identify the conditions under which AV becomes an attractive land-use option.

The remainder of the paper proceeds as follows. Section 2 presents the conceptual framework underlying the farmer's adoption and land allocation decisions, highlighting the role of risk, returns, and contract design. Section 3 describes the empirical strategy, including the joint estimation approach used to model adoption and acreage decisions. Section 4 outlines the discrete choice experiment design, followed by a description of the data in Section 5. Section 6 presents the empirical results, including marginal effects and willingness-to-accept estimates. Section 7 concludes with policy implications for scaling agrivoltaics in U.S. agricultural systems.

2. Conceptual Framework

To fix ideas, we develop a simple one-period model in which the farmer decides whether or not to allocate a portion ($x \in [0,1]$) of their L-acre farmland to a specific agrivoltaic system. Consistent with common AV arrangements, we assume that (i) the solar developer installs and maintains the PV system, and (ii) the farmer receives a fixed per-acre rental payment for the land enrolled in solar generation. Specifically, the farmer is considering the two options described as follows.

Option A (Status Quo). Under this option, the land is completely allocated for cropping, and no solar energy will be produced. Suppose the random, per-acre return of crop only is $\pi_c =$

$\mu_c + \epsilon_c$, where μ_c is the mean of crop return under the 'crop only' option, and ϵ_c is a stochastic term with $E(\epsilon_c) = 0$ and $\mathrm{Var}(\epsilon_c) = \sigma_c^2$. The total profit under this option is simply $\pi^A = L \cdot \pi_c$.

Option B (Agrivoltaics). Under this option, the farmer adopts agrivoltaics and devotes a portion ($x \in [0,1]$) of their L-acre farmland to such land use. We assume that two key specifics of AV/solar are fixed to farmers: the portion ($\rho \in [0, \hat{\rho}]$) of the AV field under solar panels and the lease payment per acre (r) from solar developers for land under solar panels. When $\rho = \hat{\rho}$, then the portion of land devoted to AV is used solely for solar energy production. In other words, we treat traditional solar energy production as an extreme case of AV. We further assume that no crop will be planted under solar panels and that no buffer area is needed between solar panels and crops in the AV system. Therefore, the portion of land for crop only is $1 - x$. Thus, the farmer's net return under Option B is:

$$\pi^B = L \cdot [(1 - x) \cdot \pi_c + x \cdot (r \cdot \rho + (1 - \rho) \cdot \pi_c - \delta)], \tag{1}$$

where δ is the per-acre switching cost from cropping only to AV, which may entail changes in crop choices, equipment, or psychological costs of forgoing the lifestyle of traditional farming. For simplicity, we assume that cropping profitability in the AV system is the same as in the cropping-only system.

It is readily checked that if $x = 0$ (i.e., the farmer will not devote any land to AV), then $\pi^B = L \cdot \pi_c = \pi^A$. That is, Option A is essentially a special case of Option B when $x = 0$. We now explore the optimal value of x that maximizes the expected utility of Option B. For simplicity, we assume that the farmer has a mean-variance utility function: $U(\pi) = E(\pi) - \frac{\lambda}{2} Var(\pi)$, where $\lambda > 0$ is the risk aversion parameter. Specifically,

$$U(\pi^B) = L \cdot [\mu_c + x \cdot (r\rho - \rho\mu_c - \delta)] - \frac{\lambda}{2} L^2 (1 - x\rho)^2 \epsilon_c^2. \tag{2}$$

Taking the derivative with respect to x yields

$$\frac{\partial U(\pi^B)}{\partial x} = L \cdot \left[\underbrace{\rho \cdot (r - \mu_c) - \delta}_{\Lambda} \right] + \lambda \underbrace{\cdot L^2 \cdot (1 - \rho x)\rho\epsilon_c^2}_{\Omega}, \quad (3)$$

where term Λ is the marginal effect of one more acre of land converted from cropping only to AV on the mean of total return on the farm. Intuitively, when one more acre of cropland is converted to AV, the net return is the difference between the solar rental payment and the crop return on the land under the solar panels, net of the conversion cost. The term Ω in Equation (3) measures the marginal effect of an increase in x on the expected utility under Option B through the channel of reducing return variance. Because both ρ and x are in $[0,1]$, we have $\Omega > 0$. Therefore, it is readily verified that if Λ>0, then we always have $(\pi B)/\partial x$>0, indicating that the optimal choice of x is 1 (i.e., devoting all acreage on the farm to the AV system). This is as expected because, given that the solar rental payment from AV is riskless, if an increase in x can raise the mean return, then the farm should convert all its land to AV. Based on equation (3), we can obtain that as long as $\Lambda > -\lambda L(1-\rho)\rho\epsilon_c^2$ then $x^* = 1$. In other words, if the utility increase caused by the variation decrease when evaluated at $x = 1$ can offset the utility decrease caused by the decline of mean returns, then it is optimal to convert all land on the farm to AV.[2]

In contrast, if $\Lambda < -\lambda L\rho\epsilon_c^2$, then for any $x \in [0,1]$ we will have $\partial U(\pi^B)/\partial x < 0$, indicating that the optimal value of x should be 0 (i.e., choosing Option A, the status quo). In this case, the decrease in mean returns is so large when converting to AV that even the largest utility increasing effect from return variation reduction ($\lambda L\rho\epsilon_c^2$) cannot offset the utility reduction caused by the decrease in mean returns. Thus, the farmer's optimal choice is the status quo.

Finally, if $\Lambda \in [-\lambda L\rho\epsilon_c^2,\ -\lambda L(1-\rho)\rho\epsilon_c^2]$, then an interior optimal solution x^* solves

[2] Note that the utility increasing effect of variation decrease is the smallest when evaluated at $x = 1$.

$$\frac{\partial U(\pi^B)}{\partial x}|_{x^*} = 0. \tag{4}$$

After some algebra, we obtain

$$x^* = \frac{1}{\rho} + \frac{\rho(r-\mu_c)-\delta}{\lambda L \rho^2 \epsilon_c^2} = \frac{1}{\rho} + \frac{\Lambda}{\lambda L \rho^2 \epsilon_c^2}. \tag{5}$$

From Equation (5), we can draw a few conclusions. First, as expected, an increase in rental payment from solar developers (i.e., r) or a decrease in the conversion cost (i.e., δ) will incentivize farmers to devote a larger portion of their farmland to AV. Second, farmers who are more risk-averse (i.e., with larger λ) are more likely to adopt AV. To see this, note that in Equation (5) we have $\Lambda < 0$. Third, an increase in the variance of crop returns (i.e., ϵ_c^2) will increase farmers' incentive to adopt the AV. An implication of this finding is that, everything else equal, lower income variability under the AV systems will increase farmers' willingness to adopt AV. Fourth, larger farms (L) are more likely to adopt AV because the variation-reduction effect is greater for farms with larger acreage. Finally, the effect of the land portion under solar panels in the AV system (i.e., ρ) is undetermined. This is because an increase in ρ has two opposing effects: one reduces expected utility by decreasing mean returns, and the other increases expected utility by decreasing return variance. Thus, the effect of ρ on x^* is an empirical question. We now explore these relationships by using data obtained from a farmer survey with choice experiments.

3. Choice experiment

The discrete choice experiment (DCE) examined five key attributes related to the adoption of solar and agrivoltaic systems, as listed in Table 1. These attributes were identified and refined through two online focus group sessions with farmers in January 2025 and validated through a pilot survey conducted during the same period. Participants in the focus groups received a $100 gift card as compensation for their time and feedback during the survey development process. The attribute levels are grounded in existing agronomic and PV literature, reflect current policy incentives, and align with previous AV adoption studies (e.g., Caplan et al., 2024; Cuppari et al., 2024; Wagner et al., 2024; Zeddies et al., 2025; Lazaridou et al., 2026). Table 1 also summarizes key attributes of AV systems relevant to the experiment's design.

Table 1: Design of the Choice Experiment

Attributes	Levels	No. of levels
Need for new farming equipment	Yes, No	2
Need to switch to new crops	Yes, No	2
Variability in annual net income compared to the status quo	0%, 50% lower	2
Portion of the field under solar panels (Land)	25%, 50%, 75%, 100%	4
Lease payment from the solar developer for the portion listed above of 1-acre field under solar panels	\$500, \$1,000, \$1,500, \$2,000	4

Each of these attributes varies across the hypothetical scenarios presented to respondents and is designed to capture key economic and operational trade-offs associated with AV adoption. Following the stated-choice literature (e.g., Louviere et al., 2000; Train, 2009), these attributes are treated as explanatory variables influencing farmers' adoption decisions and land allocation choices. Below, we describe each attribute, its economic interpretation, and its use in the experiment.

The "Need for New Farming Equipment" attribute captures whether adopting an AV system would require farmers to invest in specialized machinery beyond their existing equipment. Similarly, the "Need to Switch to New Crops" attribute indicates whether AV adoption requires switching from current crops to alternatives such as hay or specialty crops. The "Variability in Annual Net Income" attribute captures the extent to which adopting AV changes the variability (risk) of annual net income relative to the farmer's current operation. The attribute takes two levels: (i) 0%, indicating zero income variability relative to the status quo, and (ii) 50% lower, indicating that the variability of annual net income under AV is reduced by 50% relative to the status quo. The "Share of Land" attribute reflects the proportion of the field allocated to agrivoltaic or solar use, ranging from partial allocation (25%–75%) under agrivoltaics to full-field allocation (100%) under solar-only systems.[3] Finally, the "Land Lease" attribute represents the annual payment received from solar developers for the portion of the field allocated to solar energy production, with levels set at $500, $1,000, $1,500, and $2,000 per acre. This attribute captures the monetary compensation offered to farmers and corresponds to the financial incentive for adoption discussed in Section 6.

Following the stated choice literature (Louviere et al., 2000), we define each alternative in the experiment as a combination of attribute levels describing a potential agrivoltaic contract. Enumerating all possible combinations of the five attributes and their respective levels yields a full-factorial design of 128 unique profiles (2 × 2 × 2 × 4 × 4 combinations), referred to as "scenarios." A full-factorial design ensures orthogonality across attributes, allowing independent identification of main effects and selected interaction effects in the econometric model. While discrete choice models are nonlinear, prior work shows that identification of utility parameters relies on variation in attribute differences across alternatives, and the inclusion of a status quo option provides the necessary normalization for estimation (Louviere et al., 2000; McFadden, 1974).

[3] The percentage values refer to the share of the field enrolled in agrivoltaic or solar production, not the physical density of solar panel coverage. Even in solar-only systems, panels are spaced apart to allow for maintenance access and to reduce shading between panel rows.

To make the task manageable for respondents while preserving statistical efficiency, the 128 scenarios were randomized and partitioned into 8 survey versions using a blocking design commonly employed in stated-choice experiments (Louviere et al., 2000; Train, 2009). Each respondent was randomly assigned to one version, evaluating four choice sets. In each choice set, respondents were presented with a hypothetical AV contract defined by a specific combination of attribute levels and asked whether they would adopt the contract or retain their current (status quo) land use. Conditional on adoption, respondents were then asked to indicate the share (or acreage) of land they would allocate to the AV system. This structure aligns with the joint discrete–continuous decision framework modeled in Section 5.

The final design, therefore, consists of 128 contract profiles paired with a status quo alternative. This single-alternative format was selected based on pre-testing with farmers, which indicated that presenting multiple competing contracts within each choice set increased cognitive burden and reduced response quality. While this approach is less statistically efficient than designs with multiple alternatives per set, it improves respondent comprehension and completion rates, which is particularly important when eliciting both adoption and land allocation decisions. Moreover, the design preserves orthogonality across attributes and provides sufficient variation to estimate the effects of contract attributes on both stages of the decision process. This design approach has been previously used in agricultural adoption studies examining joint adoption and intensity decisions (e.g., Khanna et al., 2017). An example choice set is presented in Table 2, and the full survey questionnaire is provided in the Supplementary Materials.

Table 2: Sample choice set

For a 1-acre field, please choose between the two options presented below and respond to the statement below each scenario.

	Option B	**Option A:**
Need for new equipment	No	Keep Status Quo Crop Production
Need to switch to new crops	Yes	
Variability in annual net income compared to status quo	0%	
Portion of the field under solar panels	50%	
Lease payment from solar developer for the portion listed above of the 1-acre field under solar panels	$500	
SELECT ONE	○	○
If Option B is chosen, I would be willing to have the selected option on _____% of my operated acres, which amounts to _____acres.		

4. Data

We conducted a farmer survey between February and August 2025 using a random sample of 2,500 farmers from 12 U.S. Midwest states (Figure 1), selected from Dynata's proprietary farm database, compiled by Dynata LLC. This database includes detailed information on farm enterprises across the US. The 12 states were chosen for their prominence in corn and soybean production, their flat terrain conducive to solar energy deployment, and their variation in land returns, farm sizes, and demographics, which enable analysis of the drivers of solar and agrivoltaics adoption. We received 250 responses (10% response rate), of which 73 were excluded due to incomplete data (see Figure 1 for response rate by state). The final sample of 177 respondents forms the basis of our analysis. The survey followed Dillman's Total Design Method (Dillman, 2000). Each participant received a packet including a cover letter explaining the study, the survey instrument, and a prepaid return envelope. Participation was voluntary, and one reminder postcard was sent two weeks after the initial mailing. To encourage participation, survey respondents were offered a $2 prepaid incentive included in the survey packet and an additional $23 upon completion.

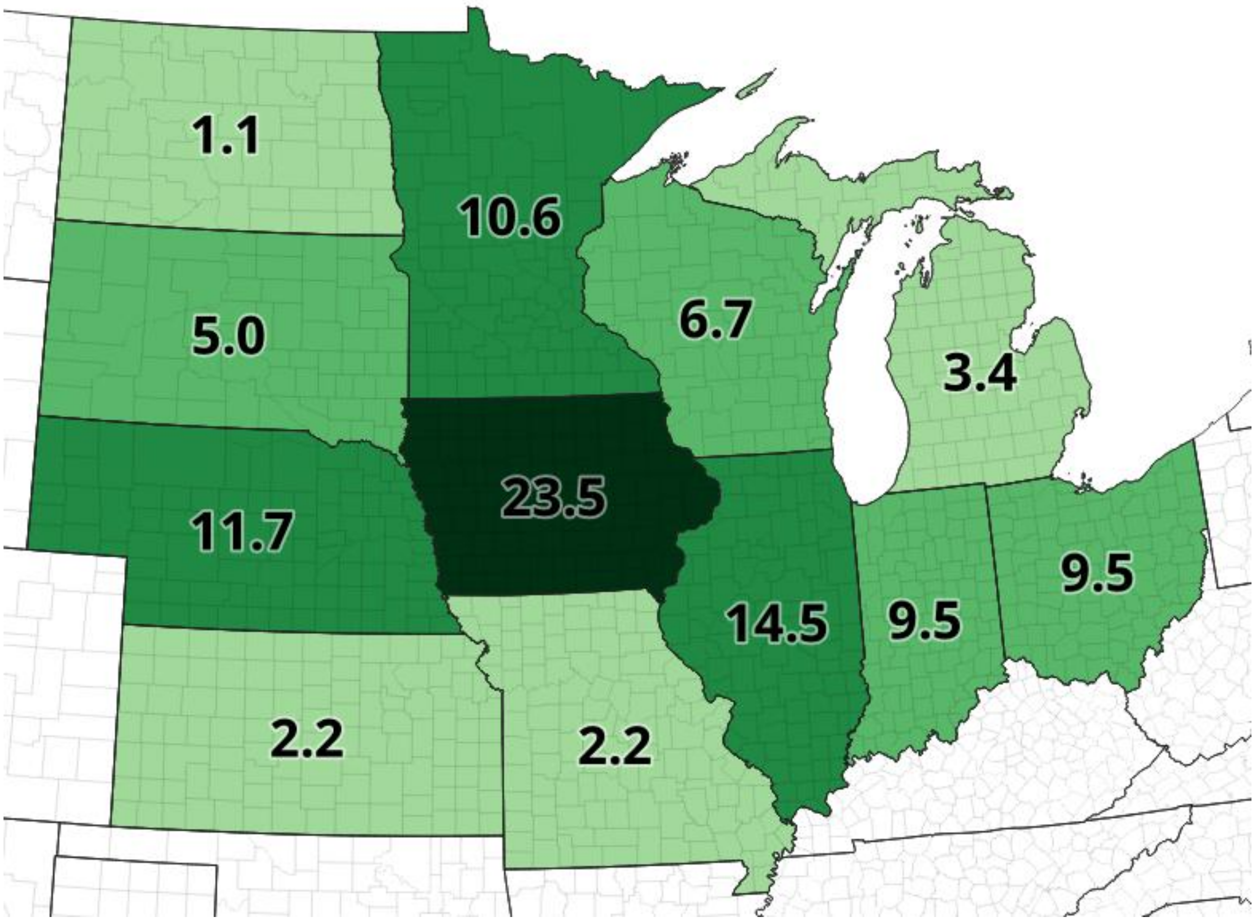

Figure 1: Geographic distribution of survey respondents across selected U.S. states (%)

Note: The figure shows the U.S. states represented in the survey sample. Data are based on responses from 177 farmers across 12 Midwestern states.

Source: Authors' survey data.

4.1 Dependent Variable Construction

The discrete choice dependent variable, "Adopt," equals 1 if the farmer is willing to convert a portion of their land to solar or agrivoltaic systems, and 0 otherwise. The continuous dependent variable, “Acres,” is defined as the number of acres the farmer is willing to convert, including zero values reported by non-adopters. To accommodate these zero observations, we apply a log transformation to *(Acres + 1)*, so that non-adopters (with zero acres) are assigned a value of *log(1) = 0*. This approach is commonly used in applications involving nonnegative outcomes with corner solutions because it preserves zero observations while avoiding the undefined log(0). Although alternative transformations, such as the inverse hyperbolic sine (IHS) transformation, have also been proposed to handle zeros (Bellemare and Wichman, 2020), our results are qualitatively robust to alternative specifications. [4] In addition to the choice attributes, we include several farm and farmer characteristics that prior studies have shown to influence technology adoption decisions (e.g., Caplan et al., 2024; Khanna et al., 2017; Wagner et al., 2024; Zeddies et al., 2025). These variables, along with their expected signs of the coefficients, are described below and summarized in Table A1 (Appendix 1).

4.2 Farmer Characteristics

Prior studies highlight the importance of risk attitudes in technology adoption decisions (Yang et al., 2015; Khanna et al., 2017). We measure farmers' risk attitude using a self-assessment question in the survey, asking respondents to characterize their management style as either: (i) cautious, (ii) willing to take risks after adequate research, or (iii) enjoying taking risks. This approach follows methods used by Dohmen et al. (2011), Roe (2015), and Khanna et al. (2017). We define the “Risk Preference” variable as a binary indicator equal to 0 for cautious farmers and 1 for those willing to take or enjoy taking risks.

[4] Results are qualitatively similar when using alternative specifications, including estimation in levels and transformations designed for zero-valued outcomes.

Time preferences are a key determinant of technology adoption, especially for investments with upfront costs and delayed returns (Duquette et al., 2013; Yang et al., 2016; Khanna et al., 2017). We measure farmers' time preference using a discount rate derived from a front-end delay task in the survey, following the approach of Coller and Williams (1999), Harrison et al. (2002), and Khanna et al. (2017). Respondents were presented with five choices, each asking whether they would prefer to receive $1,000 today or $1,000 + $X five years later (see Question 20 in the survey questionnaire in the Supplementary materials). The smallest delayed amount a respondent accepted, relative to the immediate $1,000, was used to calculate their individual discount rate, reflecting their preference for present versus future returns.

We also include several farmer-level variables to control for heterogeneity that may influence the adoption of solar and agrivoltaic systems (Wagner et al., 2024). Age is measured in years. Older farmers may be less likely to adopt these technologies due to shorter planning horizons relative to the investment payback period. Prior studies suggest that younger farmers tend to be more open to innovation, better informed, and more willing to take risks, whereas older farmers may favor technologies that offer short-term returns and lifestyle benefits (Khanna et al., 2017; Zeddies et al., 2024). Education is included as a categorical variable: 0 = "High school graduate or GED," 1 = "Some high school," and 2 = "Some college or higher." Higher educational attainment may lower the learning costs and increase awareness of the environmental and financial benefits of adopting solar technologies (Lazaridou et al., 2026).

We also include a binary variable for full-time farming status, equal to 1 if the farmer's primary income comes from farming and 0 otherwise. Off-farm income can either provide the financial flexibility to adopt new technologies or limit the time available for learning and investment. Evidence on its effect is mixed (Fernandez-Cornejo, 2007; Jensen et al., 2007; Khanna et al., 2017). Finally, we include the "Percentage of Owned Land", defined as the ratio of owned to total operated acres, to capture the role of land tenure. Farmers who rent a larger share of land may be less willing to adopt technologies requiring long-term investment (Jensen et al., 2007; Keelan et al., 2009; Khanna et al., 2017).

4.3 Farm characteristics

Several farm-level factors may influence both the likelihood of adopting solar or agrivoltaic systems and the amount of land allocated to them. Key factors include farm size and status quo returns to land (Wagner et al., 2024). Farm Size is measured as the total number of operating acres. Larger farms may be more likely to adopt AV due to economies of scale, greater access to capital, and the availability of marginal land for repurposing. Conversely, smaller farms may have stronger incentives to convert land to solar/AV due to lower input and maintenance requirements compared to conventional crops. However, empirical evidence on the relationship between farm size and solar/AV adoption remains limited (Caplan et al., 2024; Cuppari et al., 2024; Wagner et al., 2024). The "Status Quo Returns to Land" represents the opportunity cost of allocating land away from current agricultural uses. Farms earning higher net income per acre are less likely to convert land to solar/AV systems, given the higher foregone returns (Khanna et al., 2017). We measure status quo returns as the five-year average annual net income per acre from the land the farmer would consider converting, as reported in the survey.

4.4 Descriptive statistics

The completed surveys yielded data on 708 choice observations, of which solar and agrivoltaics options were selected in 112 cases, representing approximately 16% of all choice observations. Summary statistics in Table A1 (Appendix 1) show that, on average, adopters had larger farm sizes and lower status quo annual income than non-adopters. Adopters also exhibited greater risk tolerance and lower discount rates, indicating a stronger preference for long-term returns (Figure 2). In terms of choice attributes, adopters were more likely to face scenarios with higher land lease payments and a larger share of land under solar panels, and were less likely to face requirements for new farming equipment (Figure 3). Differences in crop-switching requirements and income variability were not statistically significant at the descriptive level.

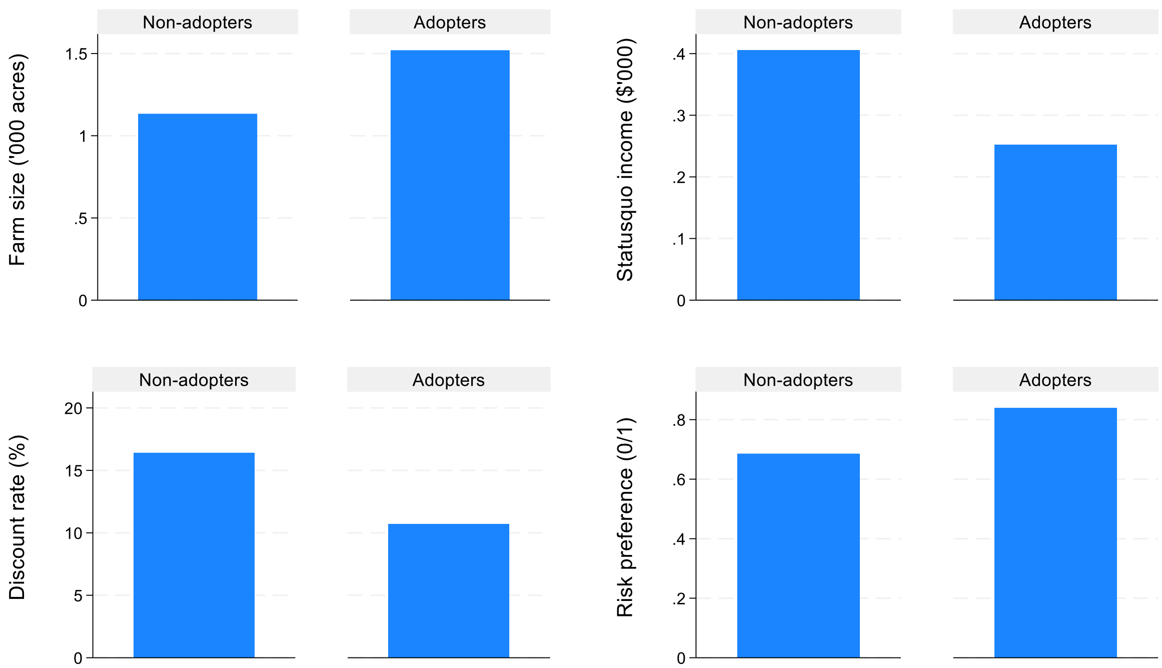

Figure 2: Mean values of farm size, status quo income, discount rate, and self-reported risk preference by adoption status

Note: Based on 708 choice observations. Adopters tend to have lower baseline farm income and exhibit greater willingness to take risks than non-adopters, suggesting that both economic conditions and behavioral traits are associated with adoption decisions. The "risk preference" measure shown here is based on farmers' self-reported management style in the survey. It should be interpreted as an empirical proxy for risk attitudes rather than the formal coefficient of risk aversion in the conceptual framework.

Source: Authors' calculations based on survey data.

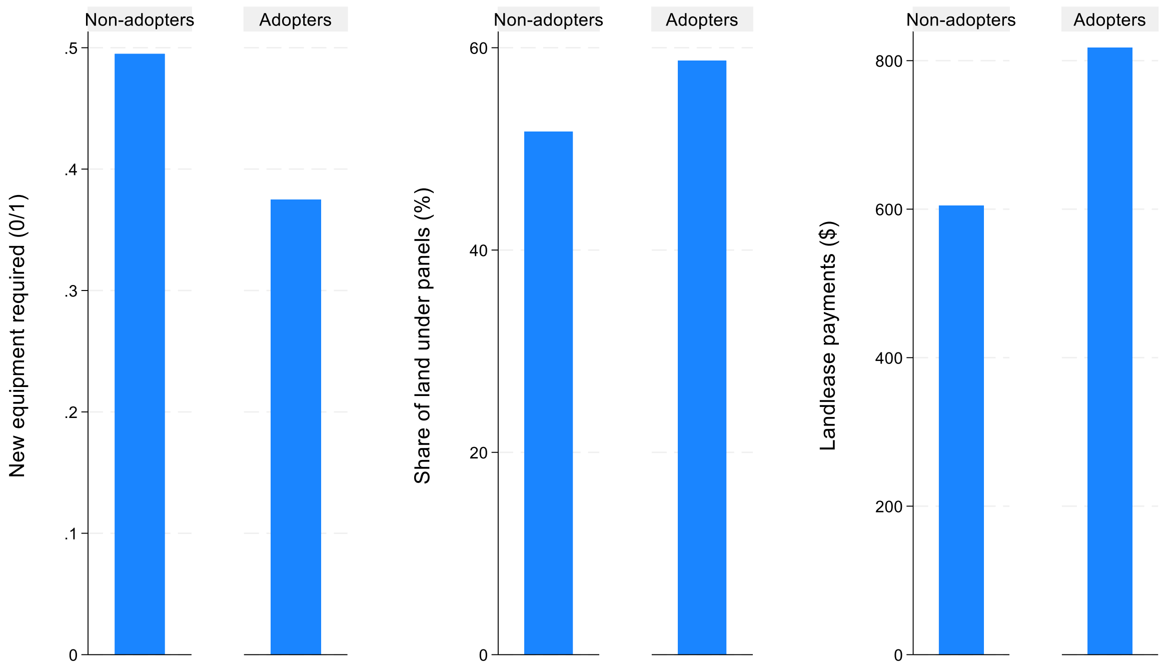

Figure 3: Mean values of key contract and technology attributes across accepted and rejected choice observations

Note: Based on 708 choice observations from the discrete choice experiment. The figure reports the mean attribute levels of the hypothetical contract scenarios associated with observations in which respondents selected the agrivoltaic/solar option ("accepted") versus retained the status quo ("rejected"). Accepted scenarios were associated with higher lease payments, larger field allocations to solar/agrivoltaic use, and lower requirements for new equipment, highlighting the importance of financial incentives and operational simplicity in adoption decisions.

Source: Authors' calculations based on survey data.

5. Estimation approach

Following Khanna et al. (2017), we estimate farmers' decisions regarding agrivoltaics and solar energy adoption as a joint discrete–continuous choice problem, where farmers first decide whether to adopt (extensive margin) and then how much land to allocate (intensive margin). Specifically, the farmer i's decision for alternative j consists of a binary adoption decision $d_{ij} \in \{0,1\}$ and a continuous acreage decision A^*_{ij}, observed only if adoption occurs. This structure reflects the sequential but interdependent nature of the decisions: adoption is a prerequisite for acreage allocation, and both decisions may be influenced by common observed and unobserved factors.

5.1 Adoption decision (discrete choice)

We estimate the adoption decision using a latent utility framework consistent with random utility theory:

$$V_{ij}^{*} = X_{ij}'\beta + v_{ij} \tag{6}$$

$$d_{ij} = \begin{cases} 1, & \text{if } V_{ij}^{*} > 0 \\ 0, & \text{otherwise} \end{cases}$$

where V_{ij}^{*} is the latent net utility gain from adopting solar/agrivoltaics relative to the status quo, X_{ij} represents explanatory variables including contract attributes and farmer/farm characteristics, β is a vector of parameters to be estimated, and the error term v_{ij} is assumed to be normally distributed, $v_{ij} \sim N(0,1)$. Adoption occurs when the expected discounted utility from agrivoltaics exceeds that of the status quo crop-only production. In the terms specified in the conceptual framework, this indicates that $U(\pi^{B})|_{x=x^{*}} > U(\pi^{A})$, where π^{B} and π^{A} denote profits under agrivoltaics/solar (Option B) and conventional crop production (Option A), respectively.

5.2 Acreage decision (continuous choice)

Conditional on adoption, farmers choose the amount of land allocated to agrivoltaics/solar:

$$A_{ij}^{*} = Z_{ij}'\gamma + \varepsilon_{ij} \tag{7}$$

$$A_{ij} = \begin{cases} A_{ij}^{*}, & \text{if } d_{ij} = 1 \\ 0, & \text{otherwise} \end{cases}$$

where A_{ij}^* is the latent desired acreage, Z_{ij} represents explanatory variables including contract attributes and farm/farmer characteristics, γ is a parameter vector, and ε_{ij} is normally distributed with $\varepsilon_{ij} \sim N(0, \sigma^2)$. This specification allows the determinants of acreage to differ from those influencing adoption, while still permitting overlap in explanatory variables.

5.3 Joint estimation and error correlation

A key feature of this framework is that unobserved factors may jointly influence both decisions. For example, attitudes toward renewable energy or risk preferences may affect both the likelihood of adoption and the extent of land allocation. To account for this, we allow the error terms to be correlated:

$$\begin{pmatrix} v_{ij} \\ \varepsilon_{ij} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma\right)$$

where Σ is an unrestricted covariance matrix. We estimate the system jointly using a recursive mixed-process model, following Roodman (2011). This approach accommodates mixed dependent variables (binary and continuous), allows for correlated disturbances across equations, and yields consistent and efficient full-information maximum likelihood estimates under joint normality. The recursive structure captures the fact that acreage choices are meaningful only after a farmer has chosen to adopt. By modeling adoption and acreage jointly, we explicitly account for this conditional relationship rather than estimating the acreage equation on a truncated sample. Following Roodman (2011), this setup treats adoption as an observed endogenous outcome in a fully observed recursive system, enabling consistent full-information estimation.

This joint estimation framework enables us to estimate how contract attributes affect both adoption probability and land allocation, test whether the same variables have different effects across decisions, and capture unobserved heterogeneity that jointly shapes both outcomes.

Importantly, failure to account for correlation between the two decisions would lead to biased estimates, as highlighted in prior applications of joint discrete–continuous models in agricultural adoption contexts (Khanna et al., 2017).

5.4 Identification and estimation details

Identification of the model parameters relies on both functional form and variation in the explanatory variables across the adoption and acreage equations. While several covariates are common to both equations, identification is strengthened by allowing for differential effects of contract attributes and farmer characteristics on the discrete adoption and continuous acreage decisions, consistent with the recursive structure of the model.

The system of equations is estimated using full-information maximum likelihood (FIML) within a recursive mixed-process framework. Because the likelihood involves multivariate normal integrals, estimation is implemented using the Geweke–Hajivassiliou–Keane (GHK) simulator, which provides a tractable approximation to the joint probability distribution. Following standard practice (Roodman 2011), results are based on simulated maximum likelihood with 300 Halton draws, and robustness checks confirm that the parameter estimates are stable with respect to the number of draws.

All models were estimated in Stata 19 using the "cmp" command (Roodman 2011), which allows for flexible estimation of multi-equation systems with mixed dependent variables and correlated error terms. Standard errors are clustered at the respondent (farmer) level to account for repeated choice observations within individuals. In addition, we test the significance of the estimated error correlation (ψ) to assess whether joint estimation is warranted.

To facilitate interpretation, marginal effects for the adoption equation and conditional effects for the acreage equation are computed post-estimation. Where relevant, standard errors for nonlinear transformations (e.g., willingness-to-accept measures) are obtained using the delta method or bootstrapping.

5.5 Latent Class Model

The logit and probit models assume homogeneous preferences across respondents, implying that all farmers value AV attributes similarly. However, adoption decisions for emerging technologies such as AVs are likely to vary substantially among farmers due to differences in production systems, financial constraints, and perceptions of land-use trade-offs. To account for this unobserved heterogeneity in preferences, we estimate a latent class (LC) choice model. LC models segment respondents into a finite number of latent groups (classes), with each class characterized by distinct preference structures and parameter estimates (Boxall and Adamowicz, 2002; Greene and Hensher, 2003; Train, 2009).

The LC framework assumes that preferences are homogeneous within each class but differ systematically across classes. Thus, the probability that farmer i chooses alternative $j$in choice situation t is conditional on membership in latent class c, while class membership itself is probabilistic and estimated jointly with the utility parameters. Compared with standard logit models, LC models provide a flexible and policy-relevant way to identify distinct adoption profiles among farmers and to quantify heterogeneity in willingness to accept (WTA) compensation for AV adoption.

A critical step in LC estimation is determining the optimal number of classes. Following common practice in the discrete choice literature (Greene and Hensher, 2003; Scarpa and Thiene, 2005; Yoo, 2020), we estimated models with one, two, and three classes and compared model performance using the log-likelihood (LL), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent Akaike Information Criterion (CAIC), and the Lo–

Mendell–Rubin likelihood ratio (LMR-LR) test. The information criteria improved substantially when moving from a one-class to a two-class specification, indicating meaningful heterogeneity in farmer preferences. However, improvements beyond two classes were relatively small, while additional classes reduced model parsimony and interpretability. In addition, the LMR-LR test suggested that the two-class specification provided a statistically significant improvement over the one-class model. In contrast, the three-class model did not yield sufficient additional explanatory power. Therefore, the two-class model was selected as the preferred specification because it provided the best balance between statistical fit, interpretability, and practical relevance.

To facilitate interpretation of economic tradeoffs, we compute marginal willingness-to-accept (WTA) measures for each attribute. WTA represents the additional annual lease compensation required for farmers to accept a less preferred AV attribute or contractual condition. Following Train (2009) and Hole (2007), class-specific WTA estimates are derived as the ratio of the non-monetary attribute coefficient to the lease payment attribute coefficient. The unconditional WTA estimate is calculated as the probability-weighted average across latent classes:

$$WTA_{i,k} = \sum_{c=1}^{C} P_{i,c}\left(-\frac{\beta_{c,k}}{\beta_{c,lease}}\right), \tag{8}$$

where $P_{i,c}$ is the estimated probability that respondent i belongs to latent class c, $\beta_{c,k}$ is the coefficient associated with attribute k in class c, and $\beta_{c,lease}$ is the coefficient on the lease payment attribute in class c. This approach allows WTA estimates to reflect both within-class preferences and the probability distribution of respondents across latent segments.

6. Results

Table 3 reports joint estimates of the adoption (extensive margin) and acreage (intensive margin) decisions across five model specifications. The sequential specifications allow us to assess the robustness of attribute effects and the incremental contribution of behavioral, demographic, and farm-level factors. Overall, the models are jointly significant based on Wald χ^2 statistics, indicating that the included variables collectively explain both adoption and land allocation decisions. Model fit improves systematically as additional controls are introduced, as reflected in higher (less negative) log pseudo-likelihood values and lower AIC. Among the specifications, Model 4 provides the best fit, suggesting that incorporating both behavioral factors and farm structure is important for explaining farmer decision-making.

A key result across all specifications is the positive and statistically significant correlation coefficient (ψ), indicating that unobserved factors jointly influence both adoption and acreage decisions. This supports the use of a joint estimation framework, consistent with prior applications of joint discrete–continuous models in the adoption of agricultural technologies (Khanna et al., 2017; Roodman, 2011).

6.1 Contract attributes and baseline effects

Across all specifications, financial incentives emerge as the most consistent and robust determinant of adoption. The lease payment variable is positive and highly significant in both the adoption and acreage equations, indicating that higher guaranteed payments increase not only the likelihood of adoption but also the acreage allocated to agrivoltaics/solar. This finding highlights the central role of stable and predictable income streams in farmer decision-making (Cuppari et al., 2024; Pascaris et al., 2020).

Table 3: Joint Estimates of Agrivoltaics Adoption and Land Allocation Decisions among U.S. Midwest Farmers

Variables	(1)		(2)		(3)		(4)	
	Adoption	Acres	Adoption	Acres	Adoption	Acres	Adoption	Acres
New equipment required	-0.2559***	-1.7411***	-0.2743***	-0.3736***	-0.2790***	-1.8311	-0.1775*	-1.3364**
	(0.0849)	(0.6127)	(0.0878)	(0.1229)	(0.0978)	(1.1184)	(0.0986)	(0.6187)
New crops required	-0.0071	-0.0072	-0.0333	-0.0865	-0.0467	-0.2977	-0.0018	-0.0720
	(0.1069)	(0.7626)	(0.2141)	(0.1291)	(0.1655)	(0.9185)	(0.1107)	(0.7003)
Income variability	0.1045	0.5055	0.1500	0.0332	0.2061	0.7943	0.2205**	0.6473
	(0.1097)	(0.7586)	(0.2090)	(0.1275)	(0.3052)	(1.4475)	(0.1118)	(0.6872)
Share of field under solar (%)	-0.0028	-0.0154	-0.0035	-0.0026	-0.0019	-0.0121	-0.0006	-0.0022
	(0.0037)	(0.0258)	(0.0055)	(0.0035)	(0.0041)	(0.0338)	(0.0036)	(0.0225)
Lease payment ($/acre)	0.0005***	0.0036***	0.0005***	0.0006***	0.0005***	0.0033*	0.0005***	0.0031***
	(0.0002)	(0.0012)	(0.0002	(0.0002)	(0.0002)	(0.0017)	(0.0002)	(0.0011)
Discount rate			-0.0183**	-0.0217***	-0.0146***	-0.0968	-0.0158***	-0.0978***
			(0.0072)	(0.0050)	(0.0042)	(0.0718)	(0.0039)	(0.0243)
Risk preference			1.1000***	2.3648***	0.5456***	2.1294***	0.3523***	1.0382
			(0.0874)	(0.7680)	(0.1265)	(0.7723)	(0.1047)	(0.6329)
Education: Some high school					0.2859	1.5121	0.0638	1.7083
					(0.6105)	(4.0159)	(0.4304)	(2.6562)
Education: Some college or higher					0.4258**	3.3685***	0.3287*	2.7384**
					(0.1660)	(1.0736)	(0.1744)	(1.0876)
Farming income dependence					-0.0301	-0.2040	-0.1037***	-1.3582
					(0.1111)	(1.0907)	(0.0241)	(0.9141)
Farm size							0.0901**	0.5689*
							(0.0367)	(0.2960)
Status quo income ($)							-0.0008***	-0.0056***
							(0.0002)	(0.0017)

Constant	-1.0205*** (0.1811)	-7.4865*** (1.2770)	-0.4603*** (0.1616)	-0.8242*** (0.2579)	-1.5382*** (0.2963)	0.4074 (0.2886)	-1.1821*** (0.2733)	-6.3879*** (1.7705)
Correlation (ψ)	8.0833*** (0.4664)		9.5754*** (0.3340)		8.5466*** (52.9549)		7.9519*** (0.8199)	
LL	-559.97		-544.85		-527.85		-483.51	
Wald χ^2 value	26.98		99.82		60.65		751.58	
AIC	1145.94		1123.70		1095.70		1021.02	
BIC	1205.25		1200.97		1186.49		1138.26	
Observations	708		696		692		568	

Note: Coefficients reported with robust standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Models are built sequentially, from technology attributes to behavioral, socio-demographic, and farm-level controls.

In contrast, operational complexity acts as a key barrier. The requirement for new equipment is consistently negative and statistically significant across most specifications, with larger magnitude effects once additional controls are included. This suggests that the need for new capital investment and changes in farm operations discourages both participation and the scale of adoption, consistent with prior qualitative evidence on agrivoltaic adoption barriers (Pascaris et al., 2020, 2021, 2026; Rumery et al., 2024).

Other design attributes, including crop switching, income variability, and land share, are generally statistically insignificant in the baseline specification. This indicates that, in the absence of behavioral and farm-level controls, farmers respond primarily to clear economic incentives and operational constraints rather than finer design features of agrivoltaics/solar systems.

6.2 Role of behavioral factors

Introducing behavioral variables in Model 2 substantially improves model fit and provides important insights into heterogeneity in adoption decisions. First, time preferences play a central role. The discount rate is negative and highly significant in both equations, indicating that farmers who are more impatient are less likely to adopt agrivoltaics/solar and allocate less land to it. This is consistent with theoretical and empirical evidence that higher discount rates reduce adoption of technologies with large upfront investment and delayed benefits (Khanna et al., 2017; Duquette et al., 2013).

Second, risk preferences significantly influence adoption. Risk-tolerant farmers are more likely to adopt agrivoltaics/solar and, to a lesser extent, allocate more land to it. This aligns with broader evidence that adoption of novel or uncertain technologies is higher among individuals willing to bear risk (Dohmen et al., 2011; Roe, 2015).

Importantly, once we control for farmers' risk and time preferences, the negative effect of requiring new equipment becomes larger and more precisely estimated. This indicates that farmers are particularly reluctant to adopt AV systems that require additional investment or changes to their existing farming practices. In other words, the need for new equipment acts as a barrier to adoption, especially for farmers who are more risk-averse or less willing to make upfront investments.

At the same time, the correlation coefficient (ψ) remains positive and significant and increases in magnitude across specifications. This suggests that unobserved factors such as managerial ability, attitudes toward innovation, or farm-specific constraints jointly influence both the decision to adopt and the extent of land allocation. These results underscore the importance of modeling adoption and acreage decisions jointly rather than separately (Roodman, 2011).

6.3 Farm structure and selection into adoption

The inclusion of farm and demographic characteristics (Models 3–5) reveals systematic patterns of selection into adoption. Farm size has a positive and statistically significant effect, indicating that larger farms are more likely to adopt agrivoltaics and allocate more land to it. This is consistent with the presence of economies of scale, greater access to capital, and increased flexibility in allocating marginal land to new uses (Khanna et al., 2017; Wagner et al., 2024).

In contrast, higher status quo land returns significantly reduce adoption, reflecting the opportunity cost of converting productive agricultural land to agrivoltaics. Similarly, households that depend primarily on farming income are less likely to adopt agrivoltaics, suggesting that it is viewed as a diversification strategy rather than a replacement for core agricultural production. Human capital also plays a role. Farmers with higher levels of education are more likely to adopt, consistent with lower information barriers and greater capacity to evaluate new technologies

(Wagner et al., 2024). This finding aligns with Lazaridou et al. (2026), who similarly report that higher levels of education significantly increase farmers' willingness to adopt agrivoltaic systems by improving awareness and understanding of agro-energy technologies.

Overall, the results highlight three main insights. First, financial incentives dominate adoption decisions: higher lease payments consistently increase both the likelihood and intensity of adoption. Second, operational simplicity is critical: requirements that disrupt existing farming practices, particularly the need for new equipment, significantly reduce adoption. Third, behavioral and structural factors shape heterogeneity: more patient, risk-tolerant, larger, and lower-income farms are more likely to adopt, indicating that agrivoltaics/solar is particularly attractive as a long-term diversification strategy on lower-return land.

6.4 Average marginal effects

Table 4 reports average marginal effects (AMEs) from the preferred specification, translating coefficient estimates into changes in adoption probabilities. These results provide a more intuitive interpretation of the relative importance of economic, behavioral, and farm-level factors. Consistent with the coefficient estimates in Table 3, economic incentives play a central role in shaping adoption decisions. Higher lease payments are associated with a statistically significant increase in the probability of adoption: a $100 increase in per-acre lease payments raises the likelihood of adoption by approximately 1.5 percentage points, holding other factors constant. While small in marginal terms, this effect accumulates quickly at realistic payment levels, reinforcing the importance of sufficiently large and stable financial incentives for inducing adoption (Khanna et al., 2017; Cuppari et al., 2024).

Time preferences also have a quantitatively meaningful effect. Higher discount rates significantly reduce adoption probabilities, indicating that more impatient farmers are less willing to undertake investments with delayed or uncertain returns. This finding supports the interpretation of agrivoltaics as a long-term investment, where future income streams must be sufficiently valued to offset the investment and short-term adjustment costs (Duquette et al., 2013; Khanna et al., 2017).

Table 4: Average marginal effects from the preferred model

Variable	Average marginal effects (AME)
New equipment required	-0.0431 (0.0330)
New crop required	-0.0021 (0.0259)
Income variability	0.0438* (0.0269)
Share of field under solar (%)	-0.0001 (0.0009)
Lease payment ($/acre)	0.0001*** (0.0001)
Discount rate	-0.0036*** (0.0012)
Risk preference	0.08387 (0.0535)
Education: Some high school	0.0042 (0.0613)
Education: Some college or higher	0.0709* (0.0401)
Farming income dependence	-0.0678 (0.0481)
Farm size ('000 acres)	0.0245** (0.0118)
Status quo income ($)	-0.0002***

Variable	Average marginal effects (AME)
	(0.0001)

Note: Average marginal effects are reported only for the preferred specification. Marginal effects from alternative model specifications are qualitatively similar and available upon request.

Opportunity costs further influence adoption decisions. Higher status quo farm income significantly reduces the probability of adoption, suggesting that farmers with more profitable existing operations are less inclined to reallocate land toward agrivoltaics. These results support the view that agrivoltaics is more attractive as a diversification strategy on lower-return land rather than as a substitute for high-value crop production.

Human capital and scale effects are also evident. Farmers with some college education or higher are approximately 10 percentage points more likely to adopt compared to those with a high school education or less, consistent with lower information and adjustment costs. This finding is consistent with Lazaridou et al. (2026), who similarly report that higher levels of education significantly increase farmers' willingness to adopt agrivoltaic systems by improving awareness and understanding of agro-energy technologies. Larger farms are also more likely to adopt, reflecting scale advantages in absorbing fixed costs, managing operational complexity, and allocating marginal land to alternative uses (Wagner et al., 2024; Khanna et al., 2017).

In contrast, most technological attributes, such as requirements for new equipment, crop switching, or increases in land share under panels, do not exhibit statistically significant marginal effects once economic incentives and farm characteristics are controlled for. This suggests that, at the margin, adoption decisions are driven less by specific design features and more by the overall financial attractiveness and opportunity cost of agrivoltaic systems. In other words, farmers appear willing to accommodate technical adjustments provided that contracts offer sufficiently attractive and predictable returns.

6.5 Marginal willingness to accept agrivoltaic attributes

To provide an economic interpretation of adoption preferences, we derive marginal compensation measures, interpreted as willingness to accept (WTA), by normalizing attribute coefficients with respect to the lease payment coefficient (Tables 5–6). These estimates represent the annual per-acre compensation farmers would require to accept specific agrivoltaic attributes or contract conditions. Confidence intervals are obtained using nonparametric bootstrapping to account for the nonlinear transformation.

Table 5: Marginal Willingness to Accept Agrivoltaic Attributes (Bootstrapped, $/acre/year)

Attribute	**Mean WTA ($/acre/year)**	**95% CI (bootstrapped)**
New equipment required	498.50** (243.56)	[21.14, 975.87]
New crop required	-13.93 (207.69)	[-420.99, 393.15]
Income variability	203.51 (232.38)	[-254.23, 661.25]
Share of land under solar (per 1 percentage point)	5.46 (5.78)	[-5.88, 16.80]

Notes: WTA values are computed as the ratio of each attribute coefficient to the lease payment coefficient (Landlease) from the baseline probit model. Confidence intervals are obtained via nonparametric bootstrap (1,000 replications). Negative values indicate the compensation required (i.e., higher lease payments) to offset a reduction in the likelihood of adoption associated with the attribute.

The results indicate that only the requirement for new equipment yields a substantially large and economically meaningful WTA estimate, with farmers requiring approximately $498 per acre per year in additional lease payments to offset this attribute. This estimate is statistically significant and robust across specifications, reinforcing the interpretation that operational complexity is a key barrier to adoption. In contrast, WTA estimates for other attributes, including income variability, crop switching, and land share under panels, are imprecisely estimated and not statistically distinguishable from zero, with wide confidence intervals spanning both positive and negative values. Although the point estimates suggest that increased income variability may require additional compensation (approximately $220 per acre), the lack of statistical precision limits confidence in these magnitudes. Similarly, the implied compensation for crop switching and land allocation is small and economically negligible.

Overall, these results suggest that farmers' preferences are not finely differentiated across most system design attributes, but are instead driven by a small number of salient factors, most notably operational disruption and financial returns. The WTA estimates, therefore, complement the main adoption results by highlighting that reducing operational complexity, particularly avoiding the need for new equipment, is likely to be more effective than marginal adjustments to system design features. More broadly, the wide confidence intervals highlight substantial heterogeneity in preferences and suggest caution in interpreting WTA estimates as precise welfare measures; instead, they are best viewed as indicating the relative importance of different adoption barriers.

6.6 Latent class model results

Table 6 presents the estimation results from the latent class analysis (LCA) model. The model was estimated such that the probability of selecting an alternative depends on the contract attributes and the alternative-specific constant (ASC). The ASC was coded as a dummy variable equal to one for the status quo (crop-only) alternative and zero for the agrivoltaic and solar alternatives. A positive and statistically significant ASC, therefore, indicates a general preference for maintaining the status quo over adopting agrivoltaics or solar.

Unlike standard logit models, which assume homogeneous preferences across all respondents, the latent class model accounts for unobserved heterogeneity in farmer preferences by probabilistically assigning respondents into distinct preference classes. Model selection statistics supported the two-class specification as the preferred model. Relative to the one-class model, the two-class model substantially improved model fit, reducing both the AIC and BIC values while the Lo–Mendell–Rubin (LMR) likelihood ratio test strongly rejected the one-class specification ($p < 0.001$).

Table 6: Latent class model estimates for agrivoltaic adoption preferences

Variables	Class 1: Moderate adopters	Class 2: High-intensity adopters
New equipment required	-0.100	-0.090
	(0.097)	(0.128)
New crop required	0.080	0.078
	(0.099)	(0.132)
Lower income variability	0.033	0.295**
	(0.099)	(0.135)
Share of land under solar	37.364***	78.766***
	(1.014)	(0.941)
Lease payment ($/acre/year)	406.644***	1027.885***
	(17.221)	(31.383)
Alternative-specific constant (ASC)	1.899***	1.354***
Class probability	62.7%	37.3%
Log likelihood	10140.24	

Variables	Class 1: Moderate adopters	Class 2: High-intensity adopters
AIC	20310.48	
BIC	20378.92	
Number of observations	708	

Notes: Standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.10.
Class probabilities are posterior latent class membership probabilities estimated from the latent class model.
Class 1 represents the majority of respondents, with lower preferred levels of land allocation and compensation for agrivoltaic adoption. In contrast, Class 2 represents a smaller segment of farmers who require substantially higher lease payments and larger land allocations. Farmers in Class 2 are also significantly more sensitive to income variability.

The estimated results reveal two distinct groups of farmers with different agrivoltaic adoption profiles. Class 1, labeled “Moderate Adopters”, represents approximately 62.7% of the sample. Farmers in this class exhibit a strong preference for the status quo alternative, as indicated by the large positive ASC coefficient (1.899, $p < 0.01$). These respondents are associated with relatively lower preferred land allocation levels and lower compensation requirements, with mean preferred land allocation and lease payment levels of approximately 37% and $407 per acre, respectively. None of the operational attributes, including requirements for new equipment, crop switching, or income variability, were statistically significant for this group, suggesting that moderate adopters are comparatively less sensitive to specific contractual or operational changes associated with agrivoltaic adoption.

Class 2, labeled “High-Intensity Adopters”, comprises approximately 37.3% of respondents. This group is characterized by substantially higher preferred land allocation and compensation levels, with average preferred land allocation reaching nearly 79% of farmland and lease payment levels exceeding $1,000 per acre. Although this class also exhibited a positive preference for the status quo alternative (ASC = 1.354, $p < 0.01$), the coefficient magnitude was smaller than that for Class 1, suggesting relatively greater openness to agrivoltaic adoption. In contrast to Moderate Adopters, High-Intensity Adopters were significantly more responsive to income stability. The positive and statistically significant coefficient for the no-income-variability attribute (0.295, $p < 0.05$) indicates that guaranteed or more stable income streams increase willingness to adopt among this group. However, as in Class 1, the coefficients for new equipment requirements and crop switching were not statistically significant.

Overall, the latent class results highlight substantial heterogeneity in farmers' preferences for agrivoltaic systems. While most farmers remain relatively cautious and prefer to maintain conventional crop production, a sizeable subgroup appears more receptive to adopting agrivoltaic, particularly with sufficiently high lease compensation. The findings further suggest that financial incentives and income stability play a central role in shaping adoption decisions across farmer segments.

7. Conclusion

This study examines farmers' adoption decisions for agrivoltaics (AV) using a stated-choice framework that captures trade-offs among income stability, operational complexity, and lease compensation. The results show that financial incentives, particularly guaranteed lease payments, are the primary driver of adoption. Farmers respond positively to higher and more predictable revenue streams, while attributes that increase operational complexity, especially the need for new equipment, significantly reduce adoption. These findings indicate that AV is evaluated not simply as an energy investment, but as a structural change to farm operations.

Behavioral and farm-level factors introduce important heterogeneity. More patient and risk-tolerant farmers are more likely to adopt, while larger farms exhibit higher adoption rates, consistent with scale advantages and greater flexibility in land allocation. In contrast, higher status quo land returns and greater dependence on farming income reduce adoption, suggesting that AV is most attractive as a diversification strategy on lower-return land rather than as a substitute for core production. The latent class analysis further highlights this heterogeneity, identifying a majority group of cautious "moderate adopters" alongside a smaller segment of "high-intensity adopters" that is more responsive to stable income streams and higher lease payments. These findings suggest that differentiated contract structures may be necessary to engage distinct farmer segments effectively.

Willingness-to-accept estimates reinforce these findings. Farmers require substantial compensation, on the order of $500 per acre annually, to accept operational disruptions such as new equipment requirements, while other system attributes are valued imprecisely. This suggests that minimizing operational disruption is at least as important as increasing lease payments. More broadly, the results indicate that adoption decisions are driven less by fine-grained design features and more by whether contracts meaningfully improve income while preserving existing farm practices.

From a policy perspective, these findings highlight the importance of contract design and risk mitigation. Policies that support stable, transparent, and long-term lease arrangements—and that reduce uncertainty around land use and operational requirements—are likely to be more effective than uniform increases in financial incentives alone. Outreach efforts that emphasize compatibility with existing farming systems and income stabilization may further enhance adoption.

Overall, agrivoltaics can serve as a viable and scalable diversification strategy under appropriately designed economic and institutional conditions. Ensuring that contract structures align with farmer preferences for stability, simplicity, and long-term viability will be critical for scaling agrivoltaics in a way that preserves agricultural production while expanding renewable energy.

Several limitations warrant consideration. The analysis relies on stated preference data, which may not fully reflect realized behavior under actual market and policy conditions. The sample is geographically concentrated in the U.S. Midwest, and unobserved social dynamics such as local acceptance are not explicitly modeled. Future research should examine revealed adoption behavior, incorporate spatial and policy heterogeneity, and explore how farmer preferences evolve as agrivoltaic systems are deployed at scale.

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Appendix

Appendix Table 1: Descriptive statistics

Variable	Definition	Expected sign	Adopters	Non-adopters	t-statistic
Acres	Acres a farmer is willing to convert to an AV/solar system		272.14 (56.29)	0.00 (0.00)	-4.83***
Farm size	Operated acres	+/-	1519.20 (2099.82)	1132.78 (1423.46)	-1.86
Owned acres (%)	Ratio of owned land to total operated acres (%)	+/-	60.75 (35.99)	62.31 (34.90)	0.42
Status quo income	Status quo annual income ($/acre)	-	252.35 (197.77)	405.36 (423.69)	5.66***
Age	Age of the farmer (years)	-	66.40 (14.93)	69.01 (12.42)	1.73
Farming experience	Farming experience (years)	+	43.45 (17.43)	45.77 (14.22)	1.31
New equipment	New for farming equipment (1=Yes 0=No)	-	0.38 (0.49)	0.49 (0.50)	2.38**
New crops	Need to switch to a new crop (1=Yes 0=No)	-	0.48 (0.50)	0.53 (0.50)	0.87
Variability in income	Variability in annual net income compared to the status quo (0%, 50% lower)	+/-	0.42 (0.50)	0.48 (0.50)	1.11
Land share	Portion of the field under solar panels	+/-	58.71 (24.59)	51.72 (23.60)	-2.78**
Land lease	Lease payment from the solar developer for the portion of the 1-acre field under solar panels	+	817.41 (540.39)	605.03 (437.71)	-3.92***
Management style (Risk preference)	Management style (0=Cautious, 1=Willing to take risks or enjoy taking risks)	+/-	0.84 (0.37)	0.69 (0.46)	-3.86***
Time preference	Discount rate (%)	-	10.71 (11.12)	16.41 (12.54)	4.86***
Full-time farmer	Primary occupation identified as a farmer (1=Yes 0=No)	+/-	0.67 (0.47)	0.67 (0.47)	-0.10

Education	Education 0=High school graduate or GED completion 1=Some college or higher 2=Some high school	1.77 (0.63)	1.39 (0.91)	-5.37***
Next generation	Next generation is interested in continuing farming (1=Yes 0=No)	0.70 (0.45)	0.70 (0.46)	-0.08
Farming income	Farming is the household's main source of income (1=Yes 0=No)	0.71 (0.46)	0.70 (0.45)	-0.01
IA	Percentage of Iowa farmers	0.24 (0.43)	0.23 (0.42)	-0.1017
IL	Percentage of Illinois farmers	0.16 (0.37)	0.14 (0.34)	
IN	Percentage of Indiana farmers	0.04 (0.21)	0.11 (0.31)	2.62**
KS	Percentage of Kansas farmers	0.05 (0.23)	0.02 (0.13)	-1.67
MI	Percentage of Michigan farmers	0.00 (0.00)	0.04 (0.20)	4.99***
MN	Percentage of Minnesota farmers	0.12 (0.32)	0.10 (0.30)	-0.52
MO	Percentage of Missouri farmers	0.04 (0.21)	0.02 (0.13)	-1.29
ND	Percentage of North Dakota farmers	0.00 (0.00)	0.01 (0.12)	2.85**
NE	Percentage of Nebraska farmers	0.11 (0.31)	0.13 (0.33)	0.42
OH	Percentage of Ohio farmers	0.11 (0.31)	0.09 (0.29)	-0.42
SD	Percentage of South Dakota farmers	0.04 (0.21)	0.05 (0.22)	0.34
WI	Percentage of Wisconsin farmers	0.08 (0.27)	0.07 (0.25)	-0.54
No. of Observations		112	596	

Note: Mean values are reported, and standard deviations are in parentheses. The t-test is used to test for statistical differences in the mean values of each variable between adopters and non-adopters, and the t-statistic is reported in the last column.

Appendix Table 2: Model Fit Statistics and Class Membership Probabilities for Latent Class Specifications

Classes	AIC	BIC	LMR (P>LMR)	Class marginal probabilities (SE)	
1	20,148.93	20,180.86		1.00 (0.00)	
2	19,694.16	19,753.47	<0.001	0.63 (0.02)	0.37 (0.02)
3					

Note: LMR is the Lo–Mendell–Rubin-adjusted likelihood-ratio test statistic. Likelihood-ratio tests compare the given model versus the same model with one less latent class.