Making Assets Contractible: Artificial Intelligence, Identity Verification, and Transaction Costs in Livestock Insurance*

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Abstract

Many valuable assets, such as livestock, are difficult to insure or finance because their identity cannot be reliably verified at low cost. AI-based biometric technologies can relax this constraint by making asset verification more accurate and less costly. This paper studies how such technology affects identity verification and transaction costs in the context of livestock insurance. We first develop a theoretical framework in which weak identity verification allows farmers to claim losses on uninsured cattle, so that a small number of insurance contracts can cover losses arising from deaths across a larger herd. This distortion generates a downward-sloping marginal-cost curve that

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mimics adverse selection even when animals are homogeneous, leading to inefficient under-enrollment. Costly physical verification under current ear-tag technology also constrains underwriting capacity and limits the scale of insurance provision. Using administrative data from 2021–2025 covering more than two million cow-years, approximately 48,000 policyholders, and 1,700 underwriters, we find that AI exposure reduces claim rates by 0.77 percentage points (14 percent), and increases insured herd size by 0.81 cows (5 percent). We also show that AI sharply reduces underwriting time per cow. By reducing the time and physical effort required for identification, AI enables underwriters to serve more policyholders, insure more cattle, and gradually extend coverage to more distant farmers. Together, these findings show that AI can reduce missing markets by making hard-to-verify assets contractible at scale. Back-of-the-envelope calculations imply that, over the first three years of AI adoption, the technology reduced claims by about 7,750 and added roughly 497,000 insured cow-years.

1 Introduction

Livestock are economically important assets worldwide. Globally, livestock support the livelihoods of approximately 1.3 billion people, account for roughly 40 percent of agricultural output, and provide more than one-third of the world's protein supply (Food and Agriculture Organization of the United Nations, 2009). They are especially important in developing economies and constitute a large share of household wealth (Rosenzweig and Wolpin, 1993). Yet these assets are also exposed to substantial risks, especially mortality risk, which can impose large financial losses on households and farms.

In principle, financial contracts around livestock—including insurance, collateralized lending, and broader agricultural risk-management products—can help households manage these risks and unlock the value of biological assets. In practice, however, contracting on livestock is hindered by substantial frictions in identifying, verifying, and monitoring individual animals over time, beyond the conventional concerns of adverse selection, moral hazard, and other market frictions. This reflects a broader problem in developing-market finance: many contracts fail not because assets lack economic value, but because weak verification and enforcement make productive assets difficult to pledge, insure, or monitor (Besley, 1995; Giné and Yang, 2009; Karlan et al., 2014a). In livestock mortality insurance, this friction is particularly acute because insurers must verify whether a deceased animal is the same animal that was originally insured. Traditional identification technologies, such as ear tags and physical records, are costly, labor-intensive, and vulnerable to manipulation. Recent advances in artificial intelligence (AI) have transformed biometric identification into a more accurate, scalable, and cost-effective verification technology.

This paper studies the impact of AI, specifically cattle facial recognition, on fraud, transaction costs, and market outcomes in livestock insurance. We first develop a theoretical framework that formalizes the central contracting friction: imperfect and costly animal identity verification. When insurers cannot perfectly verify whether a claimed dead animal is the same animal that was insured, farmers may be able to claim losses on uninsured cattle. This identity friction distorts insurers' marginal costs because contracts are no longer perfectly tied to specific animal identities.[1] The marginal cost of insuring nth cow is not

[1] Identity verification is also necessary for herd insurance, in which coverage applies to a group of cattle. Without unique animal-level identifiers, insurers cannot reliably verify which animals have been enrolled, allowing farmers to insure only part of the herd while potentially submitting claims for deaths among uninsured cattle. Weak identity verification thus creates under-enrollment: some animals remain uninsured but

simply the actuarially fair cost, but depends on the probability that the herd experiences at least n deaths, which decreases as n increases. This generates a downward-sloping marginal cost curve that mimics adverse selection, raising claim rates and induces under-enrollment, even though cows are homogeneous in underlying mortality risk. Unlike standard adverse selection (e.g., Akerlof 1970; Einav et al. 2010), this distortion arises not from unobserved risk heterogeneity, but from the insurer's inability to verify animal identity. The resulting equilibrium therefore features inefficiently low insurance coverage. In addition to imperfect verification, we highlight a second friction: verifying animal identity is itself costly and time-consuming, imposing capacity constraints on underwriters, and limiting the scale of market-level insurance provision. A low-cost and accurate identification technology addresses both frictions. By tying coverage and claims to specific cows, it reduces fraudulent claims on uninsured animals and under-enrollment; by simplifying verification, it lowers underwriting costs and relaxes operational capacity constraints.

We examine the empirical implications of adopting AI-based cattle facial recognition at a large livestock insurer in China. The insurer operates in a city with more than one million cattle and accounts for approximately 60 percent of the local insurance market. Before adopting AI, the insurer relied primarily on ear tags to identify cattle. Underwriters visited farms, physically inspected and restrained each animal, and attached or scanned an ear tag, which is a costly process. Moreover, ear tags could be lost, damaged, or tampered with, creating scope for misidentification. The new technology instead uses computer vision to extract facial features from smartphone images and match them against records in the insurer's database, with reported identification accuracy of 95–98%. We obtain administrative underwriting and claims records from the insurer covering more than two million cow-years and approximately 48,000 policyholders. These records link individual cattle to households, claims, underwriters, and geographic locations. The linked data allow us to examine the model's two mechanisms: we use household-level claim rates and insured herd size to study verification accuracy, and underwriter productivity and geographic reach to study verification costs.

The insurer conducted a small AI pilot in 2022, made the technology broadly available in 2023, and moved to nearly universal use in 2024 and 2025. This transition generates substantial variation in initial AI exposure before use became nearly universal. Our

may nonetheless be covered in practice at the claims stage.

household-level analysis exploits differences in AI exposure during the initial rollout. Exposure in 2023 was concentrated at the two extremes: 44 percent of policyholders had no cattle processed with AI, whereas 51 percent had their entire insured herd processed with AI. This difference in adoption timing provides quasi-experimental variation in AI exposure, allowing us to identify the effects of AI.

We first examine the model's identity-verification channel using claim rates and household insured herd size. At the cow level, we find that AI-treated cows are significantly less likely to generate a claim, even accounting for the household level factors. Aggregating to the household level, we exploit within-household variation over time that leverages a one-year difference in the timing of AI adoption. We compare households that were underwritten using AI in 2023 with households that continued to be underwritten using the traditional technology in 2023 but switched to AI in 2024. We fix treatment status based on each household's 2023 AI exposure and follow the two groups over time. In 2023, the early-adopting households are exposed to AI while the later-adopting households are not; thus, the differential change in outcomes relative to the 2022 baseline captures the effect of AI. The 2021 comparison provides a pre-treatment test for differential trends between the two groups. In 2024, both groups are exposed to AI, providing an additional validation test: if the 2023 difference is driven by AI rather than persistent differences between early and later adopters, the outcome gap should attenuate once the later-adopting households also receive the technology.

We find that, in 2023, AI exposure reduces household claim rates by 0.77 percentage points, or 14 percent relative to the baseline. At the same time, it increases insured herd size by 0.81 cows, or 5 percent at household level. Taken together, these findings suggest that improved identity verification both prevents claims on uninsured cattle and encourages households to enroll a larger share of their herds formally. Both effects are concentrated in 2023, when households differed in their exposure to AI-based underwriting. The 2021 estimates show no evidence of differential pre-trends, supporting the parallel-trends assumption. By 2024, when AI use becomes nearly universal, the estimated effects attenuate and are no longer statistically significant. This convergence suggests that, once AI-based verification is broadly available, the initial treatment and control groups no longer differ meaningfully in verification technology.

Finally, we examine the productivity and distributional consequences of lower verifi-

cation costs at the underwriter level. Our time-stamp evidence indicates that AI reduces average underwriting time from approximately three minutes per cow under traditional methods to one minute per cow under AI-based underwriting, a decline of nearly 70 percent. Further, we find that early adopters immediately serve more policyholders and insure more cattle, while initially expanding geographic reach only modestly. These patterns are consistent with a combination of reduced scope for fraud coordination at both the individual and village level and frictions in rapidly identifying and onboarding distant farmers, leading to stronger short-run intensification of coverage within existing networks than spatial expansion. In contrast to the household-level results, where gains dissipate after AI becomes universal, these increases in households served and cattle insured at the underwriter level persist into the following year, when the expansion in geographic reach becomes more pronounced. This pattern suggests that underwriters subsequently extend coverage to more distant households.

Together, the results show that AI-based identity verification can reshape livestock insurance markets through precise cattle identity verification and lower transaction costs. Back-of-the-envelope calculations suggest that, over 2023–2025, AI adoption prevented approximately 7,750 invalid claims and reduced insurance payouts by RMB 65.1 million, while expanding coverage by approximately 496,943 insured cow-years and 19,223 insured household-years.

Related Literature This paper contributes to several related literatures. First, our paper contributes to the literature on asymmetric information and selection in insurance and consumer financial markets. A central insight of this literature is that consumers may differ not only in their willingness to pay, but also in their expected costs, generating selection and welfare distortions (Einav et al., 2010; Einav and Finkelstein, 2011; Einav et al., 2021; DeFusco et al., 2022; Akerlof, 1970; Rothschild and Stiglitz, 1976). Related empirical work documents selection and asymmetric information in insurance markets, credit cards, mortgages, and FinTech consumer credit (Einav et al., 2010; Agarwal et al., 2010; DeFusco et al., 2022; Gupta and Hansman, 2022). Work in agricultural insurance emphasizes similar frictions, including adverse selection, moral hazard, basis risk, and high administrative costs, among others (Skees and Reed, 1986; Nelson and Loehman, 1987; Miranda, 1991; Smith and Goodwin, 1996).

Our paper builds on this literature but emphasizes a *distinct* friction: imperfect veri-

fication of the insured object. In our setting, insurers may be unable to confirm whether a claimed dead animal is the one originally insured, creating scope for claims on uninsured animals, duplicate claims, and other forms of fraud (Townsend, 1979; Picard, 1996; Crocker and Morgan, 1998). This identity-verification problem distorts marginal costs even when cows are homogeneous in mortality risk, as a contract on one cow may effectively cover losses from a broader herd. As a result, marginal costs can resemble the downward-sloping patterns associated with adverse selection. This issue is particularly salient in livestock mortality insurance, where verifying both the occurrence of loss and the identity of the insured animal is essential.

Second, our paper contributes to the growing literature on AI and financial and insurance markets. Existing work largely examines technologies that improve prediction, screening, underwriting, and monitoring, including applications to credit scoring (Berg et al., 2020), mortgage lending (Fuster et al., 2019), algorithmic underwriting (Jansen et al., 2025), robo-advising (D'Acunto et al., 2019), financial innovation (Chen et al., 2019), and credit access (Hau et al., 2024). Despite the economic importance of insurance, evidence on the use of AI in this sector remains relatively limited. An important exception is Liu (2026), who shows in a randomized experiment that AI-generated predictions of purchase intent increase agents' sales, premiums, and commissions while also affecting consumer selection. We complement this work by studying a less explored application of AI in insurance: identity verification, which plays a central role in underwriting and claiming.

Our paper is also related to research on AI's effects on labor and productivity. AI is reshaping labor markets by automating some tasks while augmenting workers in others. With AI assistance, workers can become more productive and learn faster, with particularly large gains among less-experienced workers (Brynjolfsson et al., 2025). Evidence from financial markets further highlights human–AI complementarity (Coleman et al., 2022; Cao et al., 2024); together with Jansen et al. (2025) and Liu (2026), this literature shows that AI's effects depend on the tasks it changes and how it interacts with workers' information, discretion, and incentives.

Our paper also contributes to the literature on AI, labor, and productivity. Existing research shows that AI's effects on labor productivity depend on the tasks it changes and its interaction with workers' information, discretion, and incentives (Brynjolfsson et al., 2025; Cao et al., 2024; Jansen et al., 2025; Liu, 2026). Our setting highlights a distinct form of

AI-assisted work. Whereas much of the existing evidence concerns cognitive, desk-based tasks such as customer service (Brynjolfsson et al., 2025), programming (Peng et al., 2023), financial analysis (Lopez-Lira and Tang, 2023), and sales (Huang and Rust, 2021), which are typically conducted in digital environments, cattle facial recognition brings AI directly into the field, assisting frontline underwriters performing a physically demanding task. Beyond boosting individual productivity, this technology reshapes the scale and spatial reach of insurance provision.

Recent work in computer vision and precision livestock farming shows that deep learning can identify individual cattle using facial images, coat patterns, and video data (Andrew et al., 2021; Qiao et al., 2021). We connect this technical literature to economics by studying the deployment of biometric identification in an actual insurance market.

Finally, our paper speaks to financial inclusion and missing markets in developing economies. Livestock are among the most important assets held by rural households, yet markets that rely on these assets remain underdeveloped. A large literature argues that weak property rights, limited verifiability, and high monitoring costs constrain access to insurance, credit, and other financial services in developing countries, contributing to persistent missing markets and inefficient risk allocation (Stiglitz and Weiss, 1981; Townsend, 1994; Banerjee and Duflo, 2010). These frictions are particularly severe for biological and movable assets such as livestock, whose ownership and identity are difficult to verify at scale. Our paper contributes by showing that AI-based biometrics increase asset verifiability, enabling contracts over previously hard-to-identify assets and thereby reducing missing markets.

2 Conceptual Framework

This section develops a simple framework to clarify how AI-based cattle facial recognition affects livestock insurance markets. The model emphasizes two frictions. First, when the insurer cannot perfectly identify whether a dead cow is the same cow that was insured, farmers may insure only part of their herd while effectively claiming against deaths from the entire herd. This identity friction creates scope for insurance fraud and distorts the marginal cost of coverage. Second, identifying and underwriting cattle is costly. Underwriters must travel to farms, physically identify cattle, verify ownership and condition, and record identifying information. These transaction costs limit underwriting capacity and restrict market expansion. AI-based cattle facial recognition can relax both frictions. By

improving animal identity verification, AI reduces the ability to claim on uninsured cattle. By lowering the cost of underwriting and verification, AI also increases underwriter productivity and expands coverage.

2.1 Environment

Consider a farmer who owns N cows. Cow i dies with probability π_i. If cow i dies, the insurer pays indemnity L. The marginal cost of underwriting cow i by underwriter u is

$$MC_i = \pi_i L + c_i^u, \tag{1}$$

where $\pi_i L$ is the actuarially fair expected claim cost and c_i^u denotes the transaction cost of underwriting cow i, including travel time, labor expenses, and other underwriting costs.

Let $r \in \{T, A\}$ denote the identification technology. Technology T denotes the case in which the insurer cannot identify cow identity at all. Technology A denotes the case in which the insurer can perfectly identify cow identity, for example, with the assistance of AI-based cattle facial recognition. The distinction between T and A is a simplifying benchmark. In practice, pre-AI identification technologies may provide some information about animal identity, but are vulnerable to manipulation. We extend the model by allowing informative but imperfect technology in Appendix A.1.

To focus the role of identity verification, we assume in the baseline model that cows have homogeneous and independent mortality risks, with $\pi_i = \pi$ for all i. The total number of deaths in the herd therefore follows $X \sim \text{Binomial}(N, \pi)$. The main results remain valid when mortality risks vary across cows and deaths are correlated.

2.2 Verification Frictions

2.2.1 Identity Frictions When Cow Identity Cannot Be Verified

Consider first that the insurer cannot identify cow identity at the time of claim. In this case, insurance contracts may not be effectively tied to specific animal identities. Thus, a farmer who owns N cows may purchase only $n < N$ insurance contracts and still use those contracts to claim against deaths from the entire herd. In this environment, n indexes the number of insurance contracts purchased, not the identity of a specific cow.

If a farmer who purchases n contracts receives an indemnity for up to n deaths in the herd. The insurer's total expected claim cost is therefore

$$TC^T(n) = \underbrace{\sum_{j=1}^{n-1} \Pr(X=j)\,jL}_{\text{Fewer than n deaths: pay } jL} + \underbrace{\Pr(X \geq n)nL}_{\text{At least n deaths: pay } nL}. \tag{2}$$

The first term captures states in which fewer than n cows die, so the insurer pays only for the realized deaths. The second term captures states in which deaths exceed n, in which the insurer pays the maximum indemnity nL.

Ignoring the transaction cost, the marginal cost of the nth contract is

$$mc_n^T = TC^T(n) - TC^T(n-1) = \Pr(X \geq n)L. \tag{3}$$

Equation 3 displays the key source of distortion. When cow identity cannot be verified, the nth contract pays not only when the cow nominally insured under that contract dies, but also when that cow survives and at least n other cows in the herd die. Thus, the contract covers the nth death in the herd, yielding a marginal expected claim cost of $\Pr(X \geq n)$. Since $\Pr(X \geq n)$ declines with n, the marginal cost curve is downward sloping.

This downward-sloping marginal cost does not arise from standard adverse selection. All cows are homogeneous in mortality risk. It arises instead from imperfect identity verification, which allows each contract to cover a death anywhere in the herd rather than the death of a designated cow. The first contract pays whenever at least one cow dies, the second generates an additional payment whenever at least two cows die, and so forth. Because the probability of reaching the nth death declines with n, identity frictions make the marginal cost of coverage particularly high when only a small share of the herd is insured.

2.2.2 Accurate Identification (Assisted by AI)

When cow identity can be perfectly verified, an insurance contract is tied to the identity of a specific insured cow. Therefore, ignoring transaction costs, the claim marginal cost of an additional insured cow becomes

$$MC_n^A = \pi L. \tag{4}$$

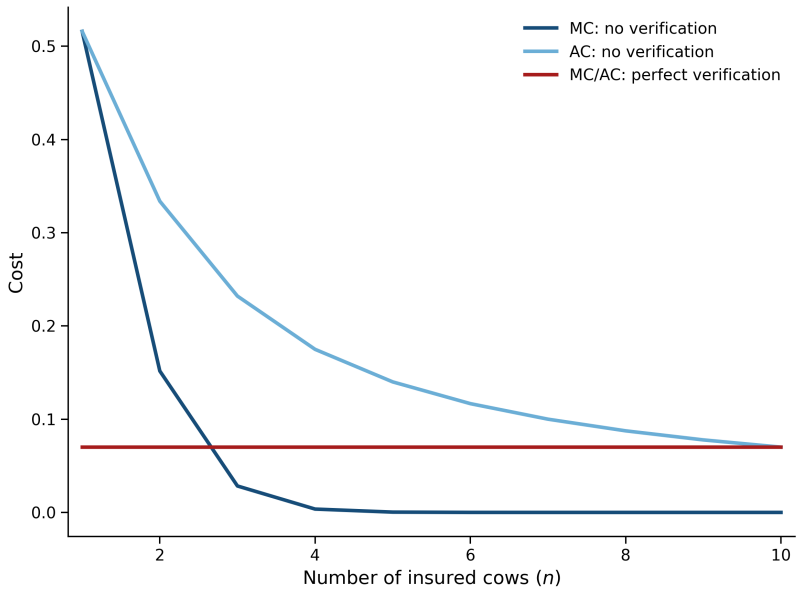
Comparing equations (3) and (4) shows the fraud-reduction channel:

$$\Pr(X \geq n)L \longrightarrow \pi L. \tag{5}$$

AI removes the value of using insured contracts to claim on uninsured cattle. As a result, AI lowers paid claim rates by limiting identity-based fraud. This effect need not reflect a decline in underlying mortality risk.

Figure illustration. We simulate the insurer's marginal and average claim costs in Figure 1, where we set $\pi = 0.07$ and normalize the indemnity to $L = 1$. Further we assume the household herd size is 10. With AI-based identification, each contract is linked to a specific cow, so the marginal claim cost is constant at $MC_n^A = \pi L$, as shown in red line in Figure 1. The dark blue line shows the marginal claim cost of the nth contract, i.e. $MC_n^T = \Pr(X \geq n)L$, under imperfect identity verification. The average claim cost, $AC^T(n) = TC^T(n)/n$, indicated as light blue line, also declines with n. It converges to the AI benchmark πL and equals it when the entire herd is insured, $n = N$. The figure therefore shows that imperfect identity verification generates a similar downward-sloping marginal cost, similar to (Einav et al., 2013), whereas AI removes this distortion and yields a flat marginal cost curve.

Figure 1: Cost Curve



(a) Identity frictions and fraud

Notes: This figure plots marginal willingness to pay and marginal cost curve. In the ear-tag regime, animal identity is imperfectly verified, so the marginal claim cost of the nth contract is $\Pr(X \geq n)L$. In the AI regime, animal identity is accurately verified, so the marginal claim cost is πL.

2.2.3 Willingness to Pay

Let the farmer have wealth w and v-NM utility $u(\cdot)$. When cow identity cannot be perfectly verified, a farmer who purchases n contracts receives coverage for the first n deaths in the herd. Let $WTP^T(n)$ denote the total premium that makes the farmer indifferent between purchasing n contracts and remaining uninsured. It is defined by

$$\underbrace{\sum_{j=0}^{n-1} \Pr(X=j)u\left(w-WTP^T(n)\right)}_{\text{Fewer than } n \text{ deaths: all losses are covered}} + \underbrace{\sum_{j=n}^{N} \Pr(X=j)u\left(w-(j-n)L-WTP^T(n)\right)}_{\text{At least } n \text{ deaths: the farmer bears the residual loss}}$$

$$= \underbrace{\sum_{j=0}^{N} \Pr(X=j)u(w-jL)}_{\text{No insurance: the farmer bears all losses}} . \tag{6}$$

The two terms on the left-hand side give expected utility with n contracts. When fewer than n cows die, all realized losses are indemnified; when at least n cows die, the farmer bears the residual loss $(j-n)L$. The term on the right-hand side gives expected utility without insurance, when the farmer bears the full loss jL.

Now suppose that cow identity can be perfectly verified, as with AI-assisted cattle facial recognition. Each insurance contract is then tied to a specific cow. If the farmer insures n cows, only deaths among those cows are covered; deaths among the remaining $N-n$ uninsured cows are not reimbursed. Let $\widetilde{X} \sim \text{Binomial}(N-n,\pi)$ denote the number of deaths among uninsured cows. Because losses on insured cows are fully indemnified, the farmer bears only the mortality risk associated with the $N-n$ uninsured cows. Let $WTP^A(n)$ denote the total premium that makes the farmer indifferent between insuring n identified cows and remaining uninsured. It is defined by

$$\underbrace{\sum_{j=0}^{N-n} \Pr(\widetilde{X}=j)u\left(w-jL-WTP^A(n)\right)}_{\text{Insure } n \text{ identified cows: bear losses only on uninsured cows}} = \underbrace{\sum_{j=0}^{N} \Pr(X=j)u(w-jL)}_{\text{No insurance: bear all mortality losses}} . \tag{7}$$

We first consider the efficient outcome. Let MC_n^r denote the marginal cost of supplying the nth contract under technology r. Insuring the nth cow is efficient whenever the farmer's

marginal willingness to pay exceeds the marginal resource cost of providing coverage. The efficient coverage quantity is therefore

$$n^r_{\text{eff}} = \max\{n \in \{1,\dots,N\} : MWTP^r(n) \geq MC^r_n\}. \tag{8}$$

Under any parameters, the marginal value of coverage exceeds its marginal cost for every cow under both identification technologies. Full coverage is therefore efficient: $n^T_{\text{eff}} = n^A_{\text{eff}} = N$. We next characterize the market equilibrium. Let AC^r_n denote the insurer's average cost per contract when the farmer purchases n contracts. Under uniform average-cost pricing, the equilibrium coverage quantity is

$$n^r_{\text{eq}} = \max\{n \in \{1,\dots,N\} : MWTP^r(n) \geq AC^{u,r}_n\}. \tag{9}$$

When cow identity cannot be perfectly verified, the first few contracts can be used to claim against deaths throughout the herd. The average cost of partial coverage consequently exceeds the marginal resource cost of expanding coverage. Under the simulated parameters, this pricing wedge causes the equilibrium quantity to fall below the efficient level:

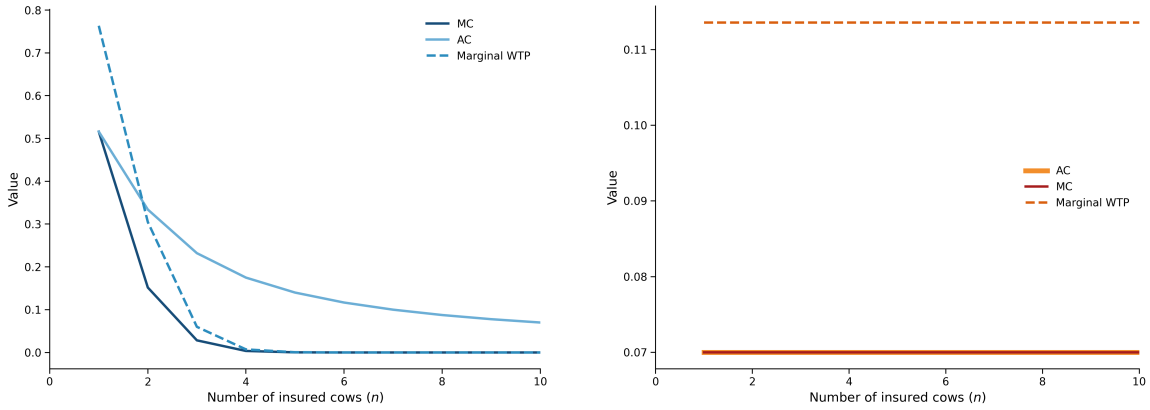
$$n^T_{\text{eq}} < n^T_{\text{eff}} = N. \tag{10}$$

Thus, although insuring the entire herd is efficient, imperfect identity verification generates under-enrollment in the market equilibrium. With accurate AI-assisted identification, each contract covers only a designated cow. Abstracting from transaction costs, average and marginal claim costs then both equal πL. The pricing wedge disappears, and the market equilibrium implements the efficient full-coverage outcome:

$$n^A_{\text{eq}} = n^A_{\text{eff}} = N. \tag{11}$$

Figure illustration. In Figure 2, we overlay the simulated marginal willingness-to-pay curves on the cost curves in Figure 1. For identification technology $r \in \{T,A\}$, define the marginal willingness to pay for the nth contract as $MWTP^r(n) = WTP^r(n) - WTP^r(n-1)$. We assumes CARA utility, $u(m) = -\frac{1}{\gamma}\exp(-\gamma m)$, where we set $\gamma = 0.0007$.

Figure 2: WTP and Equilibrium



(a) Identity frictions and fraud

(b) Transaction costs and capacity

Notes: This figure illustrates the model's equilibrium implications. Panels A and B plot marginal willingness to pay (MWTP), marginal cost (MC), and average cost (AC) as functions of the number of insured cows n. In Panel A, under the ear-tag regime, animal identity is imperfectly verified. The marginal claim cost of the nth contract is therefore $\Pr(X \geq n)L$ and declines with n. MWTP intersects AC at approximately two insured cows, implying partial enrollment even though the efficient allocation entails greater coverage. In Panel B, AI accurately links each contract to a specific cow, making both marginal and average claim costs equal to πL. Because MWTP remains above this cost for every cow, the market equilibrium achieves full enrollment and coincides with the efficient allocation. The figure uses a single household to illustrate the equilibrium mechanism and should not be interpreted as a complete market-equilibrium simulation. With households of different herd sizes, the same intuition applies after household-level marginal costs and willingness-to-pay schedules are aggregated and ordered to construct the corresponding market-level MC, AC, and MWTP curves. The simulation uses $\pi = 0.07$, $L = 1$, and CARA utility $u(m) = -(1/\gamma)\exp(-\gamma m)$ with $\gamma = 0.0007$.

2.3 Transaction Costs and Capacity

The second channel operates through transaction costs. Identifying and underwriting cattle requires underwriters to travel to farms, physically inspect animals, verify ownership and condition, and record identifying information. These tasks are labor intensive and time consuming. AI-based cattle facial recognition lowers the cost of verification, so

$$c_n^{u,A} < c_n^{u,T}. \tag{12}$$

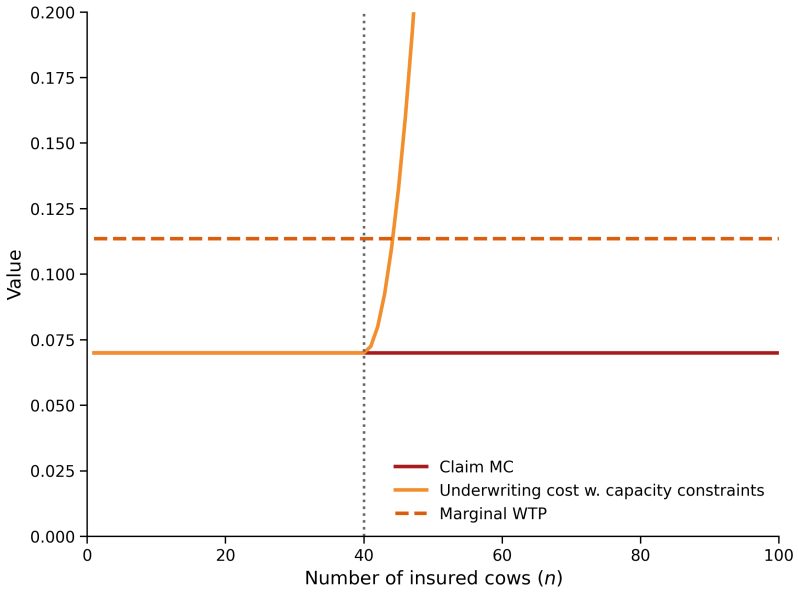
Let K^u denote the fixed time or effort capacity of underwriter u. Under identification technology r, underwriter u can serve a set of insured cows $\mathscr{I}_u^r$ subject to the capacity constraint

$$\sum_{i \in \mathscr{I}_u^r} c_i^{u,r} \leq K^u. \tag{13}$$

Because AI lowers per-cow transaction costs, the same underwriter can process more cows under accurate identification. Thus, even if AI does not change the underlying mortality risk of insured cows, it can increase insurance coverage by relaxing the underwriter's capacity constraint.

Figure 3 shows the transaction-cost channel. When cow identity is verifiable but underwriting is costly, marginal cost is shifted upward by transaction costs. AI lowers transaction costs from $c_n^{u,T}$ to $c_n^{u,A}$, shifting the marginal cost curve downward and increasing equilibrium coverage. This effect reflects improved underwriting productivity rather than a change in underlying mortality risk.

Figure 3: Transaction Cost and Capacity Constraint



Notes: This figure illustrates the model's equilibrium under underwriting-capacity constraints. Costly in-person verification adds c_n^u to the marginal cost of insuring the nth cow. To capture capacity constraints, we assume that marginal underwriting costs rise sharply once coverage exceeds 40 cows. AI lowers these costs from $c_n^{u,E}$ to $c_n^{u,A}$, shifting the marginal-cost curve downward, relaxing the capacity constraint, and expanding equilibrium coverage. The simulation sets $\pi = 0.07$ and $L = 1$, and assumes CARA utility, CARA utility $u(m) = -(1/\gamma)\exp(-\gamma m)$ with $\gamma = 0.0007$.

2.4 Empirical Predictions

Combining the , AI reduces marginal cost through two components: The framework delivers three empirical predictions through two channels with AI introduction, i.e. fraud

channel and productivity channel.

$$\underbrace{\Pr(X \geq n)L \to \pi L}_{\text{identity verification and fraud reduction}} \quad \text{and} \quad \underbrace{c_n^{u,T} \to c_n^{u,A}}_{\text{lower transaction costs}} . \tag{14}$$

First, improved identity verification reduces claim rates by preventing farmers from claiming losses on uninsured cattle; this decline reflects less identity-based fraud rather than lower mortality. Second, because a small number of contracts can no longer cover losses across the entire herd, AI increases the number of cows insured per policyholder. Third, by lowering underwriting costs, $c_i^{u,A} < c_i^{u,T}$, AI relaxes capacity constraints, allowing underwriters to insure more cows and serve more households.

3 Background and Setting

3.1 Livestock Assets and Mortality Risk

Livestock are important productive assets for households around the world. In addition to supplying meat, milk, and other animal products, they generate income, serve as a form of savings, provide collateral for borrowing, and help households cope with adverse economic shocks (Food and Agriculture Organization of the United Nations, 2009; World Bank, 2009). These functions are particularly important in developing economies, where livestock often constitute a substantial share of household wealth. Among livestock, cattle are especially valuable and economically important across countries at widely different levels of development. In the United States, cattle production generated $112.1 billion in cash receipts in 2024, accounting for approximately 22 percent of receipts from all agricultural commodities (U.S. Department of Agriculture, Economic Research Service, 2026). Cattle are also central to rural livelihoods in lower-income countries. In Ethiopia, approximately 12.5 million households depend at least partly on cattle for income, food, or draft power (Food and Agriculture Organization, 2018). In China, cattle production is also economically significant: China had more than 100 million head of cattle in 2024, making it one of the largest cattle-producing countries in the world (National Bureau of Statistics of China, 2024).

The economic value of cattle leaves livestock-owning households exposed to substantial mortality risk. Farmers face animal disease, epidemic outbreaks, natural disasters, and other shocks that can result in the death of their animals (Food and Agriculture Organiza-

tion of the United Nations, 2009; World Bank, 2009). Unlike fluctuations in output prices or current income, mortality destroys the productive asset itself and can therefore generate persistent losses in household income, wealth, and productive capacity (Dercon, 2004; Rosenzweig and Wolpin, 1993). This risk is particularly consequential for cattle because an individual animal is substantially more valuable than smaller livestock. In our setting, an adult cow represents a major household investment, and high-quality animals can be worth considerably more than other animals. The death of a cow therefore constitutes not merely a temporary income shock, but the loss of a valuable productive asset.

Figure 4: Cattle's Visible Phenotypic Traits



Notes:Source: A anonymous AI-Based cattle facial recognition company.

3.2 Cattle Mortality Insurance and the Chinese Market

Cattle insurance encompasses several distinct forms of risk protection. Some products insure cattle producers against fluctuations in prices, or operating margins, whereas others cover losses arising from disease, compulsory culling, accidents, or animal death. The product examined in this paper is cattle mortality insurance: a fixed-indemnity contract that pays a predetermined amount when a covered animal dies from an insured cause.

Livestock mortality insurance is offered in both developed and developing economies, although its institutional form varies substantially across countries. Spain's subsidized agricultural-insurance system offers cattle policies covering death or necessary slaughter arising from accidents, disease, adverse weather, and other specified causes (Agroseguro, 2026). India's National Livestock Mission similarly subsidizes insurance intended to protect livestock owners against losses from animal death, including the death of cattle and

buffalo (Department of Animal Husbandry and Dairying, 2025). Other countries rely more heavily on index-based protection against correlated herd losses. Mongolia's livestock insurance program, for example, pays when the mortality rate for a species in a local area exceeds a specified threshold, while programs in East Africa use satellite measures of forage conditions to insure pastoralists against drought-related livestock losses (World Bank, 2015; Mude et al., 2011). In the United States, by contrast, the principal federal cattle-insurance products cover price or margin risk rather than ordinary animal mortality; federal assistance for cattle deaths is generally limited to losses exceeding normal mortality from specified disasters and other eligible events (U.S. Department of Agriculture, Risk Management Agency, 2026; U.S. Department of Agriculture, Farm Service Agency, 2026). These programs illustrate an important distinction: index and disaster programs can compensate aggregate losses without identifying every dead animal, whereas individual mortality insurance requires the insurer to link each claim to a specific animal enrolled at underwriting.

China provides a particularly useful setting in which to study this individual-identification problem because cattle mortality insurance is supplied at large scale through a subsidized public–private system. Government subsidies cover most of the premium, while private insurers underwrite policies, verify cattle, and process claims. The product in our setting is a one-year mortality contract that pays a fixed indemnity when an insured cow dies from a covered cause, including disease, natural disaster, accident, attack by wild animals, complications from calving, epidemic disease, and government-mandated culling.[2] The indemnity is determined in advance and depends primarily on the animal's age, rather than on its realized market value at death. Coverage for an adult cow typically ranges from RMB 8,000 to RMB 12,000, while coverage for younger cattle is generally between RMB 2,000 and RMB 4,000. A representative adult-cow policy provides RMB 10,000 in coverage at a premium rate of 6 percent, implying an annual premium of RMB 600.[3]

Administering these insurance contracts requires animal-level verification at both underwriting and claims adjustment. Before issuing a policy, an underwriter visits the farm, verifies ownership, inspects the animal's health and eligibility, and records information intended to establish its identity. Once these requirements are completed and the farmer

[2]The insured animals in our data are primarily dairy cattle, including specialized dairy cows used mainly for milk production and dual-purpose dairy–beef cows between one and seven years of age.

[3]Premium subsidies for dairy-cow insurance are approximately 80 percent nationally, although the precise subsidy rate can vary across regions. In the region covered by our data, the subsidy rate is 80 percent throughout the sample period.

pays the farmer-financed portion of the premium, coverage takes effect. When a cow dies, the insurer must inspect the carcass, determine whether the cause of death is covered, and establish whether the dead animal is the same animal recorded at underwriting.

This last requirement distinguishes cattle mortality insurance from insurance covering people, vehicles, or real property, for which a stable administrative identifier generally exists. Cattle are living and mobile assets: they can be moved, traded, lost, replaced, or commingled with other animals, and visually similar cattle can be difficult to distinguish, as Figure 4 illustrates. Weak identification creates scope for claims on uninsured animals, repeated claims involving the same carcass, and multiple enrollment of the same animal. At the same time, costly identification can restrict insurance supply by limiting the number of animals that underwriters can process during a short underwriting season. Animal identification is therefore both an enforcement technology and a central input into the production of cattle insurance.

3.3 Traditional Identification Technology: Ear Tags

Traditionally, cattle insurers have used physical tags to link a policy record to an individual animal. The simplest technology is an external plastic tag, typically printed with a numerical or QR identifier and attached to the animal's ear, as shown in Panel (a) of Figure 5. Electronic systems instead use an RFID ear tag or, in some cases, a subcutaneous RFID transponder as shown in Panel (b) in Figure 5. At underwriting, the underwriter records or electronically scans the identifier and links it to the policy. At the claims stage, the insurer retrieves or scans the identifier on the dead animal and checks it against the underwriting record, often supplementing this comparison with a visual review of field photographs.

Ear tags improve identification, but they do not fully resolve the contracting problem. First, identification remains imperfect. External tags can fall off, become damaged, or be deliberately removed or transferred. These limitations create scope for the substitution of an uninsured animal at the claims stage and repeated use of the same carcass. When field verification relies heavily on local discretion, collusion between policyholders and insurance personnel may further weaken enforcement. Thus, a tag identifies the physical device attached to the animal, but does not always provide an immutable link to the animal's biological identity.

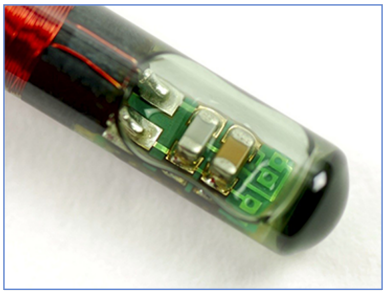
Second, ear-tag identification is costly. In our setting, the direct cost is approximately RMB 26.5 per animal: the insurer pays the underwriter RMB 20 for the tagging ser-

vice, while the electronic tag costs approximately RMB 6.5.[4] The larger cost, however, is the time and physical effort required to restrain the animal, attach an ear tag or insert a transponder, scan or record the identifier, and upload the information to the insurer's system. Panel (c) of Figure 5 shows the physical restraint required during this process. Handling large cattle is labor demanding and creates risks of injury to both workers and animals; physical restraint can also impose substantial stress on the cattle. These costs are magnified when farms are geographically dispersed and underwriting must be completed within a short seasonal window. Consequently, even when subsidies make the policy financially attractive to farmers, the verification process can constrain the number of animals that an underwriter can enroll.

Figure 5: Underwriting with Ear Tags



(a) External Plastic Ear Tag



(b) Electronic Ear Tag



(c) Injecting Electronic Ear Tag



(d) Scanning Electronic Ear Tag

Notes: This figure presents traditional cattle-identification technologies and the associated tagging process. Panel (a) shows an external plastic ear tag bearing a QR code. Panel (b) shows an electronic RFID ear tag. Panel (c) shows workers physically restraining an animal while applying an identifier. Panel (d) shows a subcutaneous RFID transponder placed near the animal's neck and the device used to read it. Panels (a) and (b) were provided by an anonymized identification-technology supplier. Panel (c) comes from a publicly available online source. Panel (d) was photographed by the authors during fieldwork.

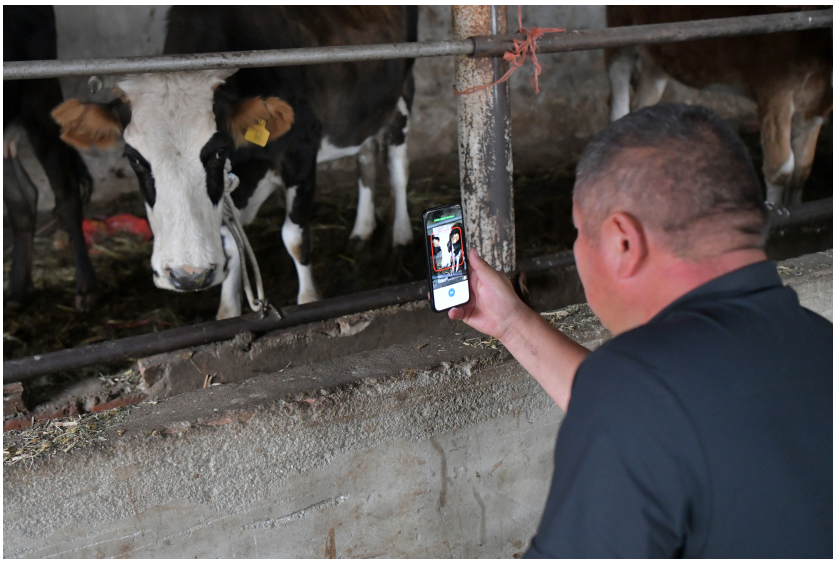
[4]Tagging-service payments and tag prices are calculated from records for the regions in our sample during 2021–2025. Prices and payment arrangements may differ modestly across regions.

3.4 AI-Based Cattle Facial Recognition

AI-based cattle facial recognition reduces the insurer's reliance on physical identifiers by linking the policy directly to the animal's visual characteristics. At underwriting, the underwriter uses a smartphone application to photograph the cow from prescribed angles, as illustrated in Figure 6. A deep-learning algorithm extracts identifying features from the animal's head and face—including coloration patterns, facial structure, and horn characteristics—and converts them into a digital representation. The system compares this representation with records in the insurer's database to detect prior enrollment and then links the verified animal to the new policy.

The same procedure is used at the claims stage. The claims adjuster photographs the dead animal, and the algorithm searches the database for the most similar enrolled record. Figure 7 illustrates this comparison between a claimed animal and its matched underwriting record. The system can also search prior claims to determine whether the same animal has already been presented for payment. According to the insurer's internal performance records, the algorithm's reported matching accuracy exceeded 98 percent during our sample period.

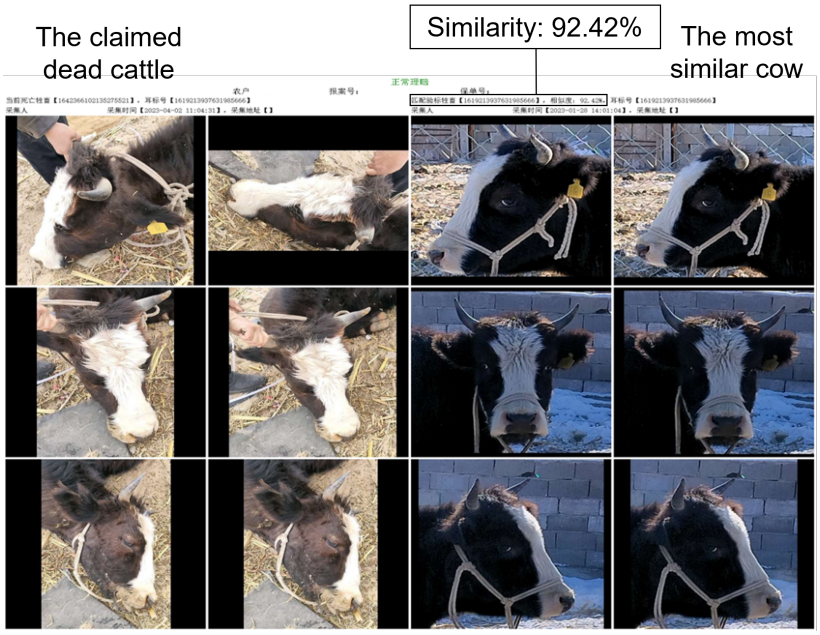
Figure 6: Underwriting with AI-Based Cattle Facial Recognition



Notes: This photograph illustrates underwriting with AI-based cattle facial recognition. The underwriter photographs the cow and verifies its identity using the insurer's smartphone application. The photograph was taken by the authors during fieldwork.

The technology changes the production of cattle insurance along two margins. First, it

Figure 7: Claims Verification with AI-Based Cattle Facial Recognition



Notes: This figure illustrates claims verification using AI-based cattle facial recognition. The claims adjuster first photographs the face of the dead animal. The algorithm extracts its visual features, searches the insurer's database, and returns the most similar enrolled animal for verification. The image was provided by the anonymized technology supplier.

strengthens identity verification by linking underwriting and claims records to the animal's biological appearance rather than exclusively to a removable physical device. This makes it more difficult to substitute an uninsured cow for an insured one or to submit repeated claims involving the same animal. Second, facial recognition lowers verification costs. Underwriters can record identity without relying solely on restraining cattle, attaching or implanting tags, operating specialized RFID readers, or manually comparing photographs. The resulting process is faster, less physically demanding, and easier to deploy at scale.

Other biometric technologies—including DNA testing, iris recognition, and muzzle-pattern recognition—can also identify cattle. In routine insurance operations, however, these methods may require biological samples, specialized equipment, close physical handling, or more time to collect and process identifying information. The relevant comparison is therefore not identification accuracy alone, but the joint ability to establish animal identity and do so at sufficiently low cost. AI-based facial recognition is attractive in this setting because it can improve the enforceability of animal-level contracts while reducing the labor and equipment required to issue them.

These operational changes correspond directly to the two frictions formalized in the

conceptual framework. More accurate identification limits the use of insurance contracts to claim losses on animals that were not enrolled, moving claim costs toward the mortality risk of the specific insured cow. Lower per-animal verification costs relax underwriters' capacity constraints, allowing a given underwriting network to process more cattle and serve more households. The institutional setting therefore motivates the paper's two principal empirical outcomes: claim rates and the scale of insurance provision.

4 Data and Descriptive Analysis

We combine several administrative datasets to study how AI-based cattle facial recognition affects fraud, transaction costs, and insurance market expansion in livestock insurance. The empirical setting is the cow insurance market in a large city in China, where the cattle inventory is estimated at approximately one million head in 2025 and the government-subsidized livestock insurance covers the risk of cattle mortality. The main sample comes from a large livestock insurer that accounts for roughly 60 percent of the local market and is one of the early adopters of AI-based cattle facial recognition. It covers 2021–2025, a period during which the focal insurer transitions from traditional ear-tag-based identification to AI-based cattle facial recognition. The data are uniquely suited for our purpose because they link insurance enrollment, animal-level attributes, claims, underwriting technology, underwriter identity, and geographic information.

Cow- and policyholder-level data. The core micro dataset is cow-level data. The data contain approximately 1.94 million cow-year observations and about 48,000 policyholders. For each insured cow, we observe policyholder identifiers, insurance dates, insured value, premium, claim outcomes, whether the cow is newly insured, whether AI facial recognition was used, and geographic location. The data also include policyholder characteristics such as age and gender.

Table 1 reports summary statistics at three levels. Panel A describes cow-year data from the local insurer. The cow-level sample has an average annual claim rate of 4.9 percent, mean coverage of RMB 8,391 per cow, and a mean premium of RMB 436. Panel B shows that, in the household-year sample, the average household insures 16.8 cows and has a claim rate of 5.5 percent. AI exposure is is approximately one-half in each sample, with values ranging from zero to one.

Table 1: Summary Statistics

	Mean	SD	Median	Min	Max
Panel A. Cow-level data					
Claim indicator	0.049	0.215	0.000	0	1
Premium per cow	436.002	135.866	462.000	0.000	1422.857
Coverage value per cow	8391.490	1913.682	8000.000	2000.000	14000.000
Newly insured cow	0.856	0.351	1.000	0	1
Distance to county government, km	38.450	27.037	31.018	0.039	254.044
Panel B. Household-year data					
Number of insured cows	16.781	15.870	13.000	1	718
Claim rate	0.055	0.109	0.000	0.000	1.000
Household AI share	0.497	0.497	0.286	0.000	1.000
Number of newly insured cows	14.371	15.133	10.000	0	718
Panel C. Underwriter-year data					
Number of insured cows	1063.722	1398.462	638.000	1	15,484
Number of households	63.449	77.536	42.000	0	778
Number of newly insured cows	910.846	1224.658	558.000	0	15,098
Number of new households	26.379	46.051	12.000	0	639
Underwriter AI share	0.518	0.483	0.708	0.000	1.000
Mean distance to households, km	35.008	23.460	30.217	0.058	220.021

Notes: This table reports summary statistics for the three main analysis datasets. Panel A uses the cow-level analysis sample. Panel B uses the household-year-level sample. Panel C uses the underwriter-year-level sample. The table reports means, standard deviations, medians, minimums, and maximums. The numbers of observations are 1,941,070 in Panel A, 115,668 in Panel B, and 1,817 in Panel C.

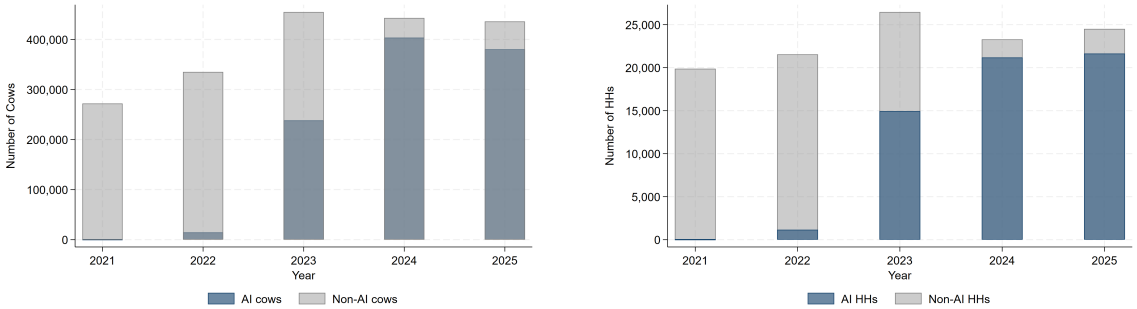
Underwriter data. We also observe underwriter-level administrative records. Underwriters are local agents, often veterinarians or animal disease-control workers, who conduct farm visits, verify cattle, record identifying information, and assist with underwriting. The data include underwriter identifiers, demographic characteristics such as gender, age, education, and measures of annual underwriting activity. By linking underwriters to insured cows and policyholders, we can measure underwriter productivity, including the number of cows and households underwritten, the number of new customers reached, and the geographic distance of served households. Panel C of Table 1 describes the underwriter-year data, At the underwriter-year level, the average underwriter serves 63 households and insures 1,064 cows, including 911 newly insured cows and 26 new households. Underwriters also differ markedly in the scale and geographic reach of their operations, providing useful variation for examining how AI affects underwriting capacity and market expansion.

AI adoption and underwriting technology. The staggered adoption of AI provides the empirical variation to examine the effects of AI. The insurer ran a very small pilot program in 2022. The technology became fully available to underwriters in 2023, but underwriters retained some discretion over whether to use it. In 2024 and 2025, the adoption became more wide. Figure 8 plots the total number of cows and households and share of cows and households underwritten using AI by year. In 2021 and 22, very few number of cows and hhs are treated with AI. In 2023, approximately 52 percent of insured cows were underwritten using AI. By 2024 and 2025, roughly 90 percent of insured cows were underwritten using AI.

AI Adoption and Underwriting Technology. The staggered adoption of AI provides the primary variation for our empirical analysis. The insurer conducted a small pilot in 2022 and made the technology broadly available to underwriters in 2023, while allowing them discretion over its use. Figure 8 plots the number and share of insured cows and households underwritten using AI in each year. AI use was negligible in 2021 and 2022 but expanded rapidly after the broader rollout: approximately 52 percent of insured cows were underwritten using AI in 2023, rising to roughly 90 percent in 2024 and 2025. Panel C shows a rapid transition from traditional to AI-based underwriting at the underwriter level. Almost no underwriters used AI in 2021, and adoption remained limited during the 2022 pilot. Following the broader rollout in 2023, a majority of active underwriters adopted the technology. By 2024 and 2025, AI use had become nearly universal among active underwriters. This adoption pattern generates substantial cross-sectional variation in AI exposure across households and underwriters in 2023, while the 2021–2025 panel allows us to examine whether claim rates and insured quantities subsequently evolved differentially with initial AI exposure.

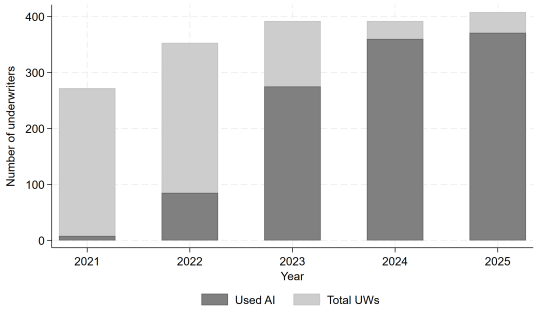
AI Adoption in 2023. We focus on AI adoption in 2023, when the technology was broadly available but not yet universally used, and examine variation across policyholders and underwriters. Panel A of Figure 9 shows that AI adoption at the policyholder level exhibits a strongly bimodal distribution: approximately 44 percent of policyholders had no cows underwritten using AI, while 51 percent had all their cows underwritten using AI. Thus, most policyholders were either fully non-AI or fully AI, with little partial adoption within policyholders. Panel B shows a similar concentration at the underwriter level, although partial adoption was somewhat more common: a larger share of underwriters used AI for

Figure 8: AI Adoption Within the Focal Insurer



(a) Cow AI exposure

(b) Household AI exposure

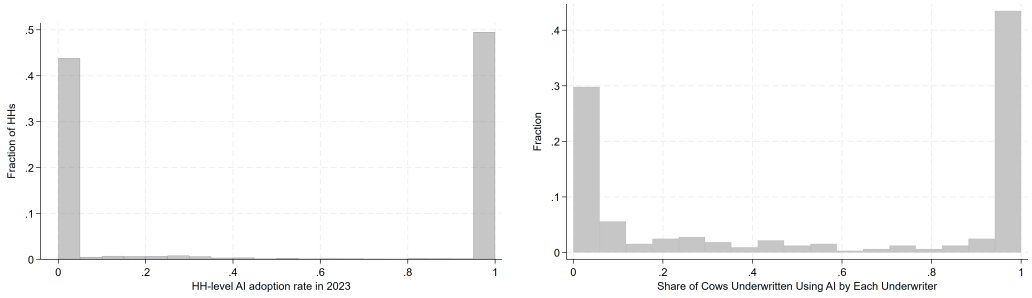


(c) Underwriter AI exposure

Notes: Panel A plots the total number of insured cows in each year and the share underwritten using AI. Panel B reports the total number of policyholders and the share whose cattle were underwritten using AI. Panel C plots the number of active underwriters in each year and the share using AI.

some, but not all, of the cows they underwrote.

Figure 9: AI Adoption at Policyholder and Underwriter Level in 2023



Notes: Panel A plots the distribution of the share of each policyholder's insured cows underwritten using AI in 2023. Panel B plots the distribution across underwriters of the share of cows underwritten using AI.

5 Empirical Evidence

This section presents the empirical evidence on how AI-based cattle facial recognition changes the operation of livestock insurance markets. The analysis is organized around the two frictions in the model. First, AI improves animal identity verification and reduces identity-based fraud. Second, AI lowers the transaction cost of underwriting, relaxes underwriter capacity constraints, and expands insurance coverage.

5.1 AI and Claim Rates: Evidence on Identity-Based Fraud

The first prediction of the model is that AI-based identification should reduce claim rates by limiting claims involving cattle that were not insured We start by presenting descriptive evidence on AI adoption and claim outcomes. We begin with descriptive evidence and then examine whether the relationship remains after accounting for observable differences across cows and unobservable differences across households.

Panel A of Figure 10 presents a simple cow-level comparison for 2023. The average claim rate is 6.61 percent among cows underwritten using AI and 6.98 percent among cows underwritten using traditional methods, a difference of 0.37 percentage points, corresponding to a 5.31 percent lower claim rate relative to the non-AI mean.

Panel B of Figure 10 and Appendix Table 1 report estimates of the relationship between AI use and cow-level claims in 2023, based on the following specification:

$$Claim_{ih} = \beta AI_{ih} + X'_{ih}\Gamma + \mu_h + \varepsilon_{ih}, \tag{15}$$

where $Claim_{ih}$ is an indicator for whether cow i in household h had a claim in 2023, and AI_{ih} indicates whether the cow was underwritten using AI. The vector X_{ih} includes the cow- and household-level controls, and μ_h is household fixed effects. Standard errors are clustered at the household level.

We introduce the controls and fixed effects sequentially. The first specification includes no controls and reproduces the raw difference shown in Panel A. The second specification controls for coverage value per cow, household insured herd size, and whether the cow is newly insured. These variables account for observable differences in cow type, household scale, and the composition of insured cattle.

A remaining concern is that AI use may be correlated with unobserved household characteristics that also affect claim risk, including herd management, local disease conditions,

farmer type, or the household's propensity to file claims. The third specification therefore includes household fixed effects, comparing AI and non-AI cows insured by the same household in the same year. This specification absorbs all observed and unobserved determinants of claims that are common across cattle within a household. The fourth specification further restricts the sample to households that used both AI and traditional underwriting in 2023. This restriction makes the identifying variation especially transparent: the AI coefficient is estimated exclusively from households in which AI- and traditionally underwritten cows can be compared directly, excluding households with no within-household variation in AI use, which cannot identify the AI effect directly but may still influence it indirectly through the estimated coefficients on the covariates

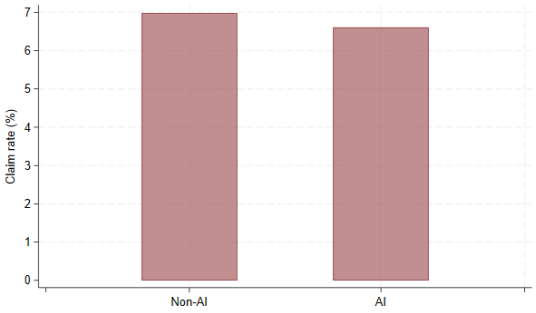
Across all four specifications, cows underwritten using AI have lower claim rates. The estimated relationship becomes larger in magnitude after household fixed effects are included. In the restricted within-household sample, AI underwriting is associated with a 1.25-percentage-point reduction in the probability of a paid claim. Relative to the 6.98 percent claim rate among non-AI cows, this estimate represents a decline of approximately 17.9 percent. Overall, the results are consistent with the model's prediction that stronger animal-level identification is associated with lower claim rate.

Although the within-policyholder comparison provides suggestive evidence, it may not isolate the causal effect of AI adoption. AI processing was not randomly assigned across cows within a household, so the estimates may reflect unobserved differences between cows selected into AI and traditional underwriting. Moreover, the comparison relies on the relatively small subset of cows in households that used both methods in 2023. We therefore interpret these estimates as suggestive evidence consistent with the identity-verification mechanism and turn to a broader panel design that exploits changes in AI exposure over time. Specifically, we estimate the following event-study specification at the household-year level:

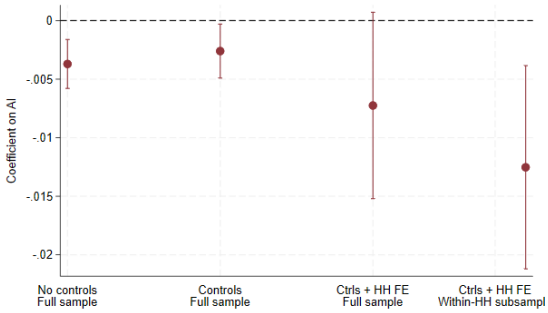
$$ClaimRate_{ht} = \sum_{k \neq 2022} \beta_k \mathbf{1}\{t = k\} \times AI_{h,2023} + X'_{ht}\Gamma + \mu_h + \lambda_t + \varepsilon_{ht}. \tag{16}$$

Here, $ClaimRate_{ht}$ is the claim rate for household h in year t, and $AI_{h,2023}$ is an indicator of whether household h's in 2023 was processed using AI. The omitted year is 2022, immediately before AI became broadly available. The household fixed effect μ_h absorbs time-invariant differences across households, such as persistent herd management prac-

Figure 10: AI and Cow-Level Claim Rates in 2023



(a) Cow-level claim rate: AI vs. non-AI



(b) Regression estimates of the effect of AI on claim rates

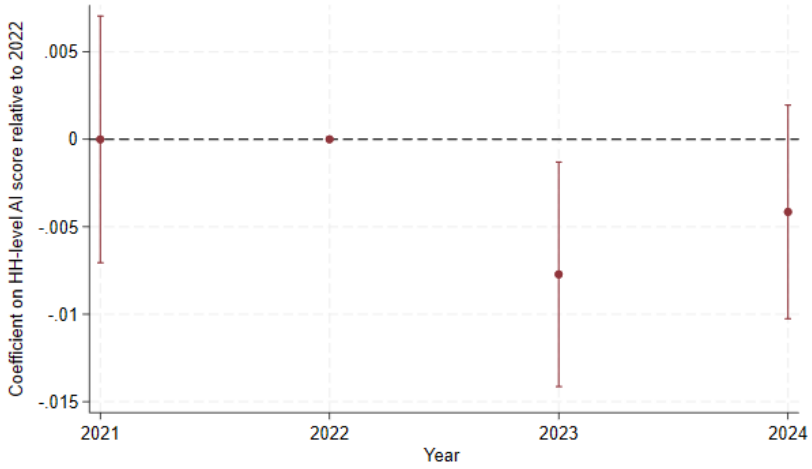
Notes: This figure presents descriptive and regression estimates on the relationship between AI underwriting and claim outcomes using cow-level data from 2023. Panel A plots the mean cow-level claim rate for cows underwritten using traditional methods (non-AI) and cows underwritten using AI. Panel B plots estimates of the coefficient on the AI indicator, AI_{ih}, from Equation 15. The first three specifications use the full sample and include, sequentially: (1) no controls; (2) controls for coverage value per cow, household insured herd size, and whether the cow is newly insured; and (3) the same controls and household fixed effects. The fourth specification restricts the sample to households that used both AI and traditional underwriting in 2023 and includes the controls and household fixed effects. Standard errors are clustered at the household level. Vertical bars in Panel B indicate 95% confidence intervals. Standard errors are clustered at the household level, and the vertical bars in Panel B denote 95% confidence intervals.

tices, location, farmer type, and long-run claim propensity. The year fixed effect λ_t absorbs aggregate changes in policy, disease risk, cattle market conditions, and claim-processing rules. The vector X_{ht} includes time-varying household-level controls.

This specification should not be interpreted as a standard staggered-adoption difference-in-differences design. The treatment variable, $AI_{h,2023}$, is fixed based on AI exposure in 2023. It does not continue to measure differential treatment intensity in later years, especially because AI adoption becomes close to universal after 2023. Instead, the coefficients β_k describe whether households with higher AI exposure in 2023 experienced differential changes in claim rates relative to households with different 2023 AI exposure. The pre-2023 coefficients provide a diagnostic check for differential pre-trends, while the later-year coefficients should be interpreted more cautiously. Since most policyholders eventually adopt AI, we expect the differential effect between high- and low-2023-AI households to diminish over time. Our findings are conceptually distinct from conventional adverse selection. The AI technology does not assess cattle health, predict mortality, or screen animals based on their underlying risk;it only verifies identity during underwriting and claims pro-

cessing. The lower claim rate therefore does not arise because AI enables the insurer to select healthier cattle.

Figure 11: AI Exposure and Household Claim Rates Over Time



Notes: This figure reports coefficients from Equation (16). The dependent variable is the household-year claim rate. The key explanatory variables are interactions between year indicators and $AI_{h,2023}$, the share of household h's insured cows in 2023 that were processed using AI. The omitted year is 2022. The specification includes household fixed effects, year fixed effects, and household-year controls. Standard errors are clustered at the household level. Vertical bars report 95 percent confidence intervals.

The event-study evidence is consistent with the within-household cow-level result. Before broad AI adoption, households with higher and lower 2023 AI exposure do not display differential claim-rate trends: the 2021 coefficient is essentially zero and statistically insignificant. In 2023, when AI becomes broadly available but is not yet universal, the coefficient becomes negative and statistically significant. The estimate is -0.0077 with a standard error of 0.0033, implying that moving from zero to full AI exposure in 2023 is associated with a 0.77 percentage-point decline in the household claim rate relative to 2022. This corresponds to a 13.95 percent reduction relative to the baseline claim rate. In 2024, the coefficient remains negative, at -0.0042, but is no longer statistically significant. This attenuation is consistent with the fact that AI adoption becomes widespread after 2023, so the fixed 2023 exposure measure no longer captures persistent differences in treatment intensity.

5.2 AI and Household Insured Size

The model also implies that improved identity verification can change the quantity of insurance purchased by existing households. We examine household insured size using the same 2023 exposure design. For each household-year, let $Cows_{ht}$ denote the number of insured cows in household h year t. We estimate

$$Cows_{ht} = \sum_{k \neq 2022} \theta_k \mathbf{1}\{t = k\} \times AI_{h,2023} + X'_{ht}\Pi + \mu_h + \lambda_t + \nu_{ht}. \tag{17}$$

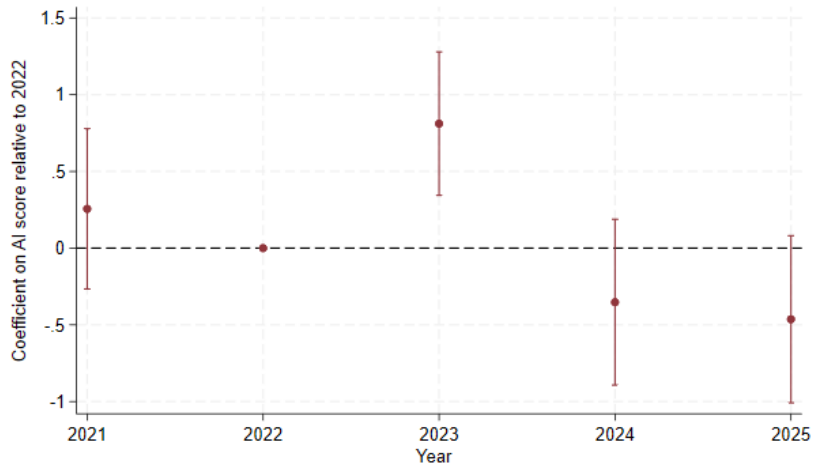
Again, the treatment variable is fixed using 2023 AI exposure, and later years should be interpreted as a test of whether differential outcomes persist once AI adoption becomes more widespread.

Figure 12 shows a sharp increase in insured herd size among households with higher AI exposure in 2023. Relative to 2022, the coefficient for 2023 is 0.811 and statistically significant at the 1 percent level. This implies that being exposed by AI in 2023 is associated with about 0.81 additional insured cows per household, or a 4.84 percent increase relative to the baseline insured herd size. In contrast, the 2021 coefficient is small and statistically insignificant, suggesting no strong differential pre-trend before broad AI availability. The coefficients in 2024 and 2025 are negative and not statistically significant at conventional levels in 2024, with only marginal significance in 2025. This pattern is consistent with a temporary differential response in 2023 that diminishes once AI becomes widely adopted across households.

The insured-size result should be interpreted jointly with the claim-rate evidence. The decline in paid claims among high-AI households suggests that AI reduces the value of using a limited number of insured contracts to claim against losses from the broader herd. At the same time, the positive 2023 effect on insured herd size indicates that AI may have increased coverage among treated households when the technology first became broadly available. Thus, the household-level quantity response does not simply reflect greater demand for insurance. It also reflects the removal of an implicit fraud opportunity and the relaxation of underwriting frictions.

The increase in insured herd size is unlikely to reflect the conventional investment response to improved insurance coverage. Prior research shows that insurance and credit provided to farmers can reduce farmers' exposure to risk and thereby encourage subse-

Figure 12: AI Exposure and Household Insured Herd Size Over Time



Notes: This figure reports coefficients from Equation (17). The dependent variable is the number of insured cows at the household-year level. The key explanatory variables are interactions between year indicators and $AI_{h,2023}$, the indicator of whether household h's insured cows in 2023 were processed using AI. The omitted year is 2022. The specification includes household fixed effects, year fixed effects, and household-year controls. Standard errors are clustered at the household level. Vertical bars report 95 percent confidence intervals.

quent investment and risk-taking (Karlan et al., 2014b). In our setting, however, insured herd size increases immediately upon AI adoption, leaving little time for enhanced risk protection to induce cattle acquisition or other real investment. The timing therefore suggests that AI allows more of a household's existing cattle to be insured, rather than inducing an expansion of the underlying herd.

5.3 AI and Underwriter Productivity

The second central prediction of the model is that AI lowers transaction costs and increases underwriting productivity. Under the traditional technology, underwriting requires travel, physical inspection, animal restraint, ear-tagging or scanning, and administrative recording. These steps are labor intensive and time consuming, which limits the number of cows and households an underwriter can process during the short underwriting season.[5]

To examine how AI affects underwriter productivity, we first assess whether it reduces the time required to underwrite each cow. By automating identity capture and verification, AI may allow underwriters to process more cattle within the short underwriting season. We estimate the following specification:

[5] As shown in Appendix Figure 2, the underwriting season in the study city is compressed into March and April by seasonal transhumance: cattle must be insured before farmers move their herds to summer pastures.

$$TimePerCow_{ut} = \sum_{k \neq 2022} \delta_k \mathbf{1}\{t = k\} \times AI_{u,2023} + X'_{ut}\Lambda + \alpha_u + \lambda_t + \eta_{ut}, \tag{18}$$

where $TimePerCow_{ut}$ is the average underwriting time per cow for underwriter u in year t.[6] $AI_{u,2023}$ denotes the share of cows processed using AI by underwriter u in 2023. Underwriter fixed effects α_u absorb permanent differences in ability, local networks, experience, and baseline productivity, while year fixed effects λ_t absorb market-wide changes in demand, policy, prices, and aggregate insurance supply. Standard errors are clustered at the underwriter level.

The coefficients δ_k capture whether underwriters with greater AI exposure in 2023 experienced differential changes in underwriting time relative to 2022. As in the household-level event-study specifications, this is not a standard staggered-adoption difference-in-differences design. The key variable $AI_{u,2023}$ is fixed using each underwriter's 2023 AI exposure. Once AI use becomes nearly universal, the coefficients for 2024 and 2025 do not identify contemporaneous treatment effects. Instead, they indicate whether underwriters with greater AI exposure in 2023 experienced different subsequent productivity trajectories than underwriters who adopted primarily in 2024.

Preliminary analysis, however, points to large productivity gains from AI. Using the time-stamp method described in Appendix B, we find that AI reduces average underwriting time per cow from about 3 minutes under the traditional process to about 1 minute under AI-based underwriting, a decline of roughly 70 percent. This large reduction is consistent with the idea that AI substantially lowers the transaction cost of verifying and recording cattle identity. In the model, this corresponds to a decline in c_i^u, which relaxes underwriter capacity constraints and allows each underwriter to serve more cows and more households.

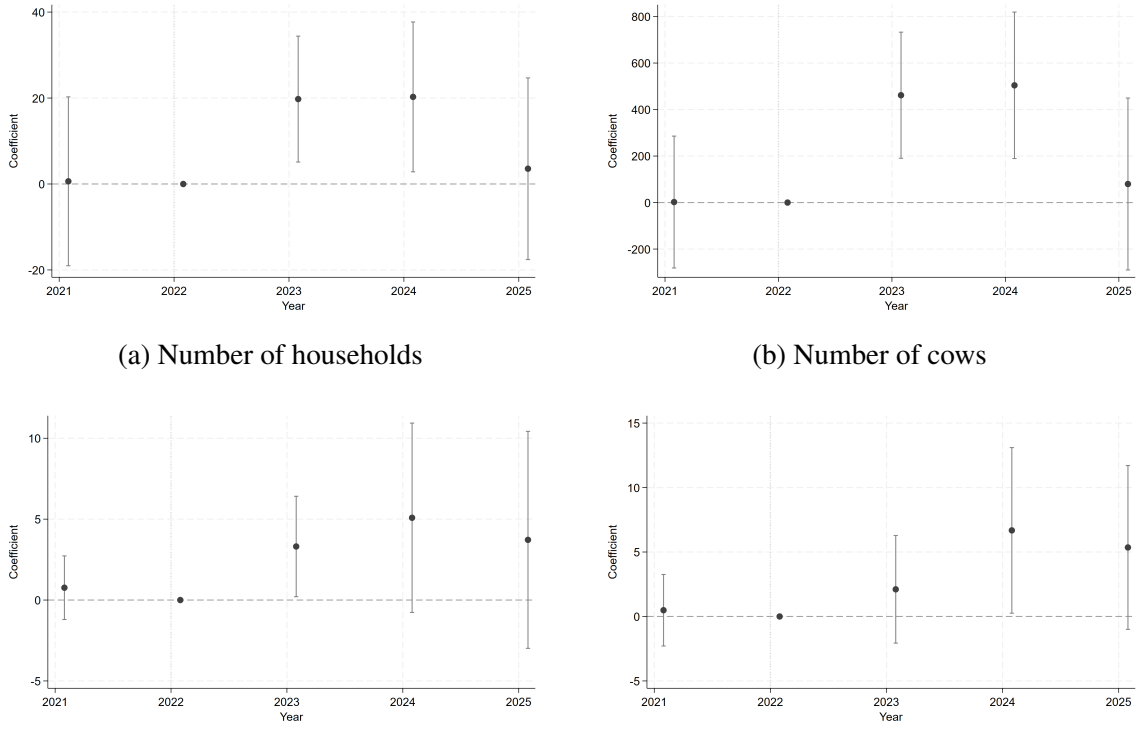
5.4 Distributional Implications of Lower Transaction Costs

We next examine whether lower transaction costs translate into greater underwriting capacity. We estimate an underwriter-level analogue of Equation (17), replacing the household-level outcome with the number of households served, the number of cows insured, the mean distance of covered households from the county center, and the 75th percentile of that dis-

[6] We construct this measure as described in Appendix B. Before AI adoption, the underwriting process generated time-stamped photographs for each household visit, allowing us to recover the elapsed time required to process a sequence of cows. After AI adoption, the data directly record a time stamp for each cow processed using AI. We use these records to construct a comparable measure of average underwriting time per cow at the underwriter-year level.

tance distribution. We restrict the sample to underwriters who had not used AI before 2023 and who adopted AI by 2024 or 2025. Because AI use became nearly universal after 2023, the 2024 and 2025 coefficients capture the persistence of differences between underwriters who adopted AI in 2023 and those who adopted later.

Figure 13: AI Exposure, Underwriting Capacity, and Geographic Reach



(a) Number of households

(b) Number of cows

(c) Mean distance

(d) 75th-percentile distance

Notes: This figure reports event-study coefficients from underwriter-year regressions using the full sample of underwriters in Equation 18. The explanatory variables are interactions between year indicators and $AIShare_{u,2023}$, the share of cows processed using AI by underwriter u in 2023. The omitted year is 2022. All specifications include underwriter and year fixed effects. Distance is measured in kilometers between the household and the relevant county government. Vertical bars report 95 percent confidence intervals based on standard errors clustered by underwriter.

Figure 13 reports the results. The 2021 coefficients are close to zero across outcomes, providing no evidence of differential pre-trends between early and later adopters. In 2023, AI adoption, measured by an indicator for any AI use, is associated with 16 additional policyholders and 413 additional cows per underwriter (a 25 percent and 39 percent increase relative to baseline means, respectively). The contemporaneous effect on geographic reach is more modest. In 2023, complete AI use is associated with an increase of approximately

3.5 kilometers in the mean distance of covered policyholders from the county center. The corresponding effect at the 75th percentile, intended to capture reaching further distance effect, is approximately 2.1 kilometers and is statistically insignificant.

Modest increase in distance suggests that the initial expansion occurred mainly within underwriters' existing local markets. This pattern is consistent with two related margins. First, by reducing the time and physical effort required to identify cattle, AI directly increases underwriting capacity, allowing underwriters to serve more policyholders during the short underwriting season. Second, the results are also consistent with a reduction in under-enrollment within local communities. Under imperfect identification, households may have had incentives to leave some cattle uninsured because deaths of uninsured animals could potentially be claimed under another policy, including a neighbor's policy. More accurate identification weakens this possibility and encourages more complete enrollment. Consistent with this interpretation, the number of insured cows rises more, and the household-level results show that AI increases the number of insured cows within a household. Thus, the initial expansion appears to reflect both broader coverage of nearby policyholders and deeper enrollment within households already connected to the local market, rather than an immediate outward expansion of the market's geographic boundary.

The coverage effects persist into 2024. Early AI adopters serve approximately 18.4 additional policyholders and insure 477 additional cows, corresponding to increases of about 29 percent and 45 percent relative to the overall means. The effects therefore last beyond the initial adoption year, even after later adopters begin using the same technology. Geographic reach also expands more clearly in 2024. The estimated effect on mean distance rises to approximately 5.1 kilometers, while the effect at the 75th percentile rises to approximately 6.7 kilometers.

The delayed increase in distance suggests that the effects of AI extend beyond an immediate reduction in processing time. Underwriters may initially use the additional capacity created by AI to expand coverage within their existing service areas. Over time, early adopters may build customer relationships, develop more efficient underwriting routes, and expand into more distant villages. The 2024 coefficients therefore capture the persistence of the initial productivity advantage and the market dynamics set in motion by early adoption.

By 2025, later adopters appear to have caught up in terms of underwriting volume. The

estimated differences fall to approximately 1.7 policyholders and 54 cows per underwriter, and neither estimate is statistically significant. This convergence is consistent with the near-universal diffusion of AI and a gradual equalization of underwriting capacity across underwriters.

The geographic effects appear to dissipate more slowly. In 2025, the estimated effect on mean distance remains positive at approximately 3.8 kilometers, although it is statistically insignificant. The effect at the 75th percentile also remains positive, at approximately 5.4 kilometers, but is imprecisely estimated. Although these estimates should be interpreted cautiously, they are consistent with persistence in the spatial organization of the market. Customer relationships and geographic networks established by early adopters may continue to shape where they operate even after later adopters catch up in the total number of policyholders and cows they serve.

These results illustrate that the productivity effects of AI encompass more than a one-period reduction in underwriting time. AI directly lowers the time and physical effort required to process each cow, but it can also increase enrollment within existing policyholders, facilitate the acquisition of new policyholders, generate learning, and alter the geographic allocation of underwriting activity. The overall pattern is one of an immediate expansion in coverage in 2023, persistent effects on both coverage and geographic reach in 2024, and convergence in underwriting volume by 2025, with more persistent differences in geographic reach. AI therefore affects not only current underwriting capacity but also the subsequent evolution of the insurance market.

6 Back-of-the-Envelope Value of AI

We combine our reduced-form estimates with the observed scale of AI use to quantify its aggregate effects on claims and insurance coverage. Over 2023–2025, the estimates imply that AI prevented approximately 7,750 claims and reduced insurance payouts by RMB 65.1 million, while expanding coverage by approximately 496,943 insured cow-years and 19,223 insured household-years

These calculations should be interpreted as back-of-the-envelope measures of the accounting and resource value of AI rather than as a complete welfare analysis. Reduced claim payments may partly represent transfers among farmers, the insurer, premium payers, and the government, while the insured value of the additional cows is not itself social surplus. A complete welfare calculation would require households' willingness to pay for

marginal insurance coverage and the real resource costs of providing that coverage. Appendix C reports the detailed calculations.

6.1 Reduction in Invalid Claims

Our household-level estimates indicate that exposure to AI reduces the claim rate by 0.7721 percentage points. Scaling this estimate by approximately 1.004 million AI-processed cow-years during 2023–2025 implies that AI prevented approximately 7,750 claims. Applying the prevailing indemnity of RMB 10,000 per cow in 2023 and RMB 8,000 per cow in 2024 and 2025 yields an estimated reduction in claim payments of RMB 65.1 million.

This calculation assumes that, in the absence of AI, the claim-rate reduction estimated during the 2023 transition year would have persisted among the households subsequently processed using AI in 2024 and 2025. It also assumes that AI affects observed claims through improved identity verification rather than through changes in the underlying mortality rate.

6.2 Expansion in Insurance Coverage

We quantify the expansion in insurance coverage using the underwriter-level estimates together with the observed number of AI-active underwriters in each adoption cohort and calendar year. The aggregate expansion can arise along three margins: more complete enrollment of cows within households already insured, participation by additional households in villages already served by the insurer, and expansion toward more distant households and villages. We return to these margins below.

Our underwriter-level design compares underwriters who adopted AI in 2023 with those who adopted in 2024. In 2023, this comparison identifies the first-year effect of AI. In 2024, both cohorts use AI, but the 2023 cohort has one additional year of experience. The 2024 coefficient therefore captures the additional expansion associated with a second year of AI use, and the cumulative second-year effect is the sum of the 2023 and 2024 coefficients.

The estimates imply that AI increases coverage by 16 households and 413 cows per underwriter in the first year of use. The estimated second-year increment remains statistically significant and is accompanied by further increases in the number of households served, the number of cows insured, and underwriting distance. The cumulative effect in the second year therefore rises to 34.4 households and 890 cows per underwriter. Because the estimated third-year differences are small and statistically insignificant, we assume that the effects plateau after the second year.

Accounting for underwriter entry, exit, and discontinuation of AI use, and aggregating the estimates across active AI underwriters, implies that AI generated approximately 3,120 additional insured household-years and 80,535 additional insured cow-years in 2023; 7,210 additional household-years and 186,393 additional cow-years in 2024; and 8,894 additional household-years and 230,015 additional cow-years in 2025. The cumulative expansion over 2023–2025 is therefore approximately 19,223 insured household-years and 496,943 insured cow-years.

Sources of Coverage Expansion. The expansion can occur along three margins. First, AI can increase enrollment within households already participating in the market. When cow identity cannot be reliably verified, a household may insure only part of its herd while retaining the possibility of claiming the death of an uninsured cow under an existing policy. By linking each policy and claim to a specific animal, AI reduces the value of partial enrollment and encourages households to insure a more complete share of their herds.

Second, improved verification can increase participation among additional households within villages already served by the insurer. Reliable animal identification limits claims involving uninsured cows or dead animals substituted across households, making coverage more enforceable at both the cow and household levels. AI can therefore support enrollment by more households within existing local markets.

Third, AI reduces the time and physical effort required to underwrite each cow, relaxing underwriters' capacity constraints during the short underwriting season. Underwriters can consequently process more cows, serve more households, and eventually travel farther. The relatively large initial increases in cows and households, together with the more modest increase in distance in 2023, suggest that early expansion was concentrated largely within existing service areas. The larger distance effects in subsequent years indicate that AI also facilitated expansion toward more remote households and villages.

These margins can be summarized as

$$\Delta Q_t = \underbrace{\sum_{h \in \mathscr{H}_{t-1}} \Delta q_{ht}}_{\substack{\text{more complete enrollment} \\ \text{within existing households}}} + \underbrace{\overline{q}_t^L \Delta H_t^L}_{\substack{\text{additional households} \\ \text{in existing local markets}}} + \underbrace{\overline{q}_t^R \Delta H_t^R}_{\substack{\text{additional households} \\ \text{in more distant markets}}}. \tag{19}$$

where $\mathscr{H}_{t-1}$ denotes households already insured before the expansion, Δq_{ht} is the increase in cows insured within an existing household, and ΔH_t^L and ΔH_t^R denote additional

households in existing local markets and more distant markets, respectively. Improved verification is central to the first two margins, while lower transaction costs facilitate both the expansion in households served and the extension of coverage to more distant locations.

7 Conclusion

This paper studies how AI-based biometric identification affects fraud, transaction costs, and market coverage in livestock insurance. We show that weak animal identification creates a distinctive contracting friction: when insurers cannot reliably link claims to insured cattle, a small number of contracts may cover losses arising from deaths across a larger herd. This distorts insurers' marginal costs and contributes to under-enrollment. At the same time, physical verification under ear-tag technology is costly and labor intensive, constraining underwriting capacity and limiting insurance provision.

Using the rollout of cattle facial recognition at a large Chinese livestock insurer, we find that AI reduces claim rates by approximately 14 percent and increases insured herd size by about 5 percent. AI also substantially reduces underwriting time, allowing underwriters to serve more policyholders, insure more cattle, and gradually extend coverage to more distant farmers. Back-of-the-envelope calculations suggest that, over the first three years of adoption, AI prevented approximately 7,750 invalid claims and added roughly 497,000 insured cow-years.

These findings highlight a broader role for AI in financial markets. Its value need not come only from improving prediction or automating decisions. By making difficult-to-verify assets identifiable at low cost, AI can strengthen contract enforceability, reduce operational frictions, and expand access to financial services. In settings where valuable biological or movable assets remain difficult to insure or finance, improvements in verification technology may therefore help make these assets contractible at scale and reduce missing markets.

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Online Appendix (Not For Publication)

A Model Extension

A.1 Informative but Imperfect Identification

Let $r \in \{T, A\}$ denote the identification technology and let $q_r \in [0,1]$ denote its accuracy. With probability q_r, the insurer can correctly link a submitted claim to the identity of an insured cow. With probability $1 - q_r$, the available identifying information is insufficient to distinguish insured from uninsured cows, so the farmer can use the purchased contracts to claim against deaths from the herd as a whole.

Technology T provides informative but imperfect identification:

$$q_T \in (0,1). \tag{20}$$

AI-based cattle facial recognition improves identification accuracy, so that

$$q_A > q_T. \tag{21}$$

The benchmark of perfect identification corresponds to $q_A = 1$. The limiting case $q_T = 0$ recovers the environment in which cow identity cannot be verified at all. Thus, the formulation nests the two polar cases while allowing the pre-AI technology to provide imperfect identification.

To isolate the identity-verification mechanism, suppose that cows are homogeneous, with $\pi_i = \pi$ for all i, and let

$$X \sim \text{Binomial}(N, \pi) \tag{22}$$

denote the total number of deaths in the herd.

A.1.1 Expected Claim Costs under Imperfect Identification

Suppose the farmer purchases $n \leq N$ insurance contracts. When identity is successfully verified, each contract covers a specific insured cow. The insurer's expected claim cost is therefore $n\pi L$. When identity cannot be verified, the n contracts can instead be used to claim against up to the first n deaths in the entire herd. Expected claim costs under technology r are therefore

$$TC^r(n) = q_r n\pi L + (1-q_r)\mathbb{E}[\min\{X,n\}]\,L$$
$$= q_r n\pi L + (1-q_r)\left[\sum_{j=0}^{n-1} j\Pr(X=j) + n\Pr(X\geq n)\right]L. \tag{23}$$

The claim marginal cost of the nth contract is

$$mc_n^r = TC^r(n) - TC^r(n-1)$$
$$= [q_r\pi + (1-q_r)\Pr(X\geq n)]\,L. \tag{24}$$

Including the transaction cost of underwriting the nth cow, the insurer's full marginal cost is

$$MC_n^{u,r} = [q_r\pi + (1-q_r)\Pr(X\geq n)]\,L + c_n^{u,r}. \tag{25}$$

Equation (24) is a weighted average of the marginal claim costs under perfect and completely uninformative identification. If identity is verified, the marginal contract covers the death of one specified cow and has expected claim cost πL. If identity is not verified, the marginal contract pays whenever the herd experiences at least n deaths and has expected claim cost $\Pr(X\geq n)L$.

[Identification accuracy and claim costs] Suppose $0<\pi<1$ and $1\leq n\leq N$.

1. If $q_r<1$, the claim marginal cost is decreasing in the number of contracts:

$$mc_{n+1}^r - mc_n^r = -(1-q_r)\Pr(X=n)L \leq 0. \tag{26}$$

2. The effect of greater identification accuracy on the marginal claim cost is

$$\frac{\partial mc_n^r}{\partial q_r} = [\pi - \Pr(X\geq n)]\,L. \tag{27}$$

Greater accuracy lowers the marginal claim cost of early contracts for which $\Pr(X\geq n)>\pi$, but may raise the marginal cost of later contracts for which $\Pr(X\geq n)<\pi$.

3. For any partial-insurance allocation, $n < N$, greater identification accuracy lowers the insurer's expected claim payment per contract.

Proof. The first result follows from $\Pr(X \geq n+1) - \Pr(X \geq n) = -\Pr(X = n)$. Differentiating equation (24) establishes the second result.

For the third result, define the expected claim rate per contract as

$$CR^r(n) = \frac{TC^r(n)}{nL} = q_r\pi + (1-q_r)\frac{\mathbb{E}[\min\{X,n\}]}{n}. \tag{28}$$

For $n < N$,

$$\frac{\mathbb{E}[\min\{X,n\}]}{n} > \pi. \tag{29}$$

To see this, consider any fixed set of n cows. The number of deaths within this set is weakly smaller, state by state, than $\min\{X,n\}$ and has expectation $n\pi$. The inequality is strict with positive probability when $n < N$. It follows that

$$\frac{\partial CR^r(n)}{\partial q_r} = \pi - \frac{\mathbb{E}[\min\{X,n\}]}{n} < 0. \tag{30}$$

□

The proposition clarifies the fraud-reduction mechanism. Imperfect identification allows a partially insured farmer to draw claims from deaths among both insured and uninsured cattle. Increasing q_r limits this possibility and therefore lowers the average paid claim rate whenever the herd is not fully insured. When $n = N$, all cows are insured and identification accuracy does not affect total expected claim costs:

$$TC^r(N) = N\pi L. \tag{31}$$

Thus, the predicted reduction in claims arises from eliminating claims on uninsured cattle rather than from reducing underlying mortality.

A.1.2 Willingness to Pay

Let the farmer have wealth w and utility $u(\cdot)$. Under technology r, with probability q_r the contracts are tied to n specific insured cows, so the farmer bears losses only from deaths among the remaining $N-n$ cows. Let

$$\widetilde{X}_n \sim \text{Binomial}(N-n, \pi) \tag{32}$$

denote the number of deaths among uninsured cows. With probability $1-q_r$, the contracts cover the first n deaths in the herd, regardless of cow identity.

The farmer's willingness to pay for n contracts, $WTP^r(n)$, therefore solves

$$\begin{aligned}
&q_r \sum_{j=0}^{N-n} \Pr(\widetilde{X}_n = j) u(w - jL - WTP^r(n)) \\
&\quad + (1-q_r) \left[\sum_{j=0}^{n-1} \Pr(X=j) u(w - WTP^r(n)) \right. \\
&\qquad\qquad \left. + \sum_{j=n}^{N} \Pr(X=j) u(w-(j-n)L - WTP^r(n)) \right] \\
&= \sum_{j=0}^{N} \Pr(X=j) u(w-jL).
\end{aligned} \tag{33}$$

Define marginal willingness to pay as

$$MWTP^r(n) = WTP^r(n) - WTP^r(n-1). \tag{34}$$

Equilibrium coverage is characterized by the largest n satisfying

$$MWTP^r(n) \geq MC_n^{u,r}. \tag{35}$$

Improved identification affects both sides of this condition. It reduces the farmer's ability to use a small number of contracts to cover deaths from the entire herd, thereby lowering the value of partial insurance. At the same time, it reduces the insurer's expected claim cost for the early contracts that are most exposed to identity-based claims. Identification accuracy alone therefore need not unambiguously increase equilibrium coverage.

A.2 Transaction Costs and Underwriting Capacity

AI also lowers the transaction cost of identifying and underwriting cattle:

$$c_n^{u,A} < c_n^{u,T}. \tag{36}$$

Combining the identity-verification and transaction-cost channels, the change in the full marginal cost of the nth contract is

$$MC_n^{u,A} - MC_n^{u,T} = (q_A - q_T)\left[\pi - \Pr(X \geq n)\right]L + \left(c_n^{u,A} - c_n^{u,T}\right). \tag{37}$$

The first term captures the effect of improved identity verification. It lowers the cost of early contracts that would otherwise be used to claim against deaths from the entire herd. The second term captures the reduction in underwriting and verification costs. Because this second term is negative across the coverage distribution, it relaxes underwriters' capacity constraints and allows them to insure more cattle and serve more policyholders.

The model therefore delivers two distinct empirical predictions. First, among partially insured households, greater identification accuracy reduces paid claim rates by preventing claims on uninsured cattle. Second, lower transaction costs increase underwriting capacity and expand insurance coverage. The first prediction concerns the validity of claims; the second concerns the scale and geographic reach of insurance provision. "'

B Measuring Underwriting Time Per Cow

This appendix describes how we construct a measure of average underwriting time per cow. The measure is designed to capture the amount of time required for underwriters to process cows during a farm visit. We construct comparable measures before and after the adoption of AI-based cattle facial recognition, using the time stamps recorded in the underwriting data.

Traditional ear-tag underwriting. Before AI adoption, underwriters were required to take photos of insured cows during the ear-tag underwriting process. These photos contain time stamps, which allow us to recover the timing of underwriting activities within each household visit. For each household visit, we identify the first and last photo time stamps among the cows underwritten during the visit. We then compute the elapsed time between the first and last photo and divide it by the number of cows processed, net of the first cow. Specifically, for household visit v, we define

$$TimePerCow_v^{ET} = \frac{LastPhotoTime_v - FirstPhotoTime_v}{N_v - 1} \times U_v, \tag{38}$$

where N_v is the number of cows photographed during the household visit and U_v is the number of underwriters involved in the visit. We use $N_v - 1$ in the denominator because the elapsed time between the first and last photo captures the time intervals between consecutive cows rather than the absolute time spent on the first cow. Multiplying by U_v converts elapsed clock time into underwriter-minutes per cow when multiple underwriters are involved.

Example. Figure 1 illustrates the measurement using a traditional ear-tag underwriting visit. The first photo is taken at 10:07 and the last photo is taken at 10:21. Excluding the first cow, the visit processes nine additional cows over 14 minutes. With at least two underwriters involved, the implied average underwriting time is

$$\frac{14}{9} \times 2 = 3.11 \tag{39}$$

underwriter-minutes per cow. This example highlights the labor-intensive nature of the traditional process: cows must be physically restrained, ear tags must be checked or attached, and multiple underwriters or assistants may be needed during the visit.

Appendix Figure 1: Measuring Underwriting Time Using Photo Time Stamps



Notes: This figure shows an example of a traditional ear-tag underwriting visit. Each photo includes a time stamp. We measure the elapsed time between the first and last photo and divide by the number of intervals between cows, $N_v - 1$. We then multiply by the number of underwriters involved to obtain underwriter-minutes per cow.

AI-based underwriting. After AI adoption, the underwriting data directly record a time stamp for each cow processed using cattle facial recognition. We use the same logic to construct average underwriting time per cow. For each household visit, we calculate the

elapsed time between the first and last AI record and divide by the number of processed cows minus one. When information on the number of underwriters involved is available, we multiply by the number of underwriters to express the measure in underwriter-minutes per cow:

$$TimePerCow_v^{AI} = \frac{LastAIRecordTime_v - FirstAIRecordTime_v}{N_v - 1} \times U_v. \tag{40}$$

This creates a comparable measure of underwriting time under traditional ear tags and AI-based cattle facial recognition.

Sample restrictions and implementation. In constructing this measure, we restrict attention to household visits with at least two cows, since the elapsed-time method requires at least two time-stamped observations. We also exclude visits with missing or invalid time stamps and winsorize extreme values to reduce the influence of data-entry errors, unusually long interruptions, or visits that combine multiple unrelated tasks. When a household has multiple underwriting visits within a year, we compute visit-level underwriting time first and then aggregate to the household-year or underwriter-year level using cow-count weights.

Interpretation. The resulting measure should be interpreted as the average amount of underwriter time required to process an additional cow during a household visit. It is not a pure measure of the physical time spent attaching an ear tag or scanning a cow. Instead, it captures the combined time required for identification, recording, and verification during the underwriting process. This is the relevant object for our analysis because the model's transaction-cost channel concerns the effective labor and time cost of underwriting cows. A decline in this measure after AI adoption provides direct evidence that AI lowers underwriting transaction costs and relaxes underwriter capacity constraints.

C Detailed Back-of-the-Envelope Calculations

C.1 Reduction in Invalid Claims

Our household-level estimate of the effect of full AI exposure on the claim rate is

$$\widehat{\beta}^{\text{claim}} = -0.007721. \tag{41}$$

Let H_t^{AI} denote the number of households processed using AI in year t, and let $\overline{N}$ denote

the average number of insured cows per household. The number of AI-processed cow-years in year t is

$$Q_t^{AI} = H_t^{AI}\overline{N}. \tag{42}$$

The corresponding number of claims prevented by AI is

$$\Delta C_t = \left|\widehat{\beta}^{\text{claim}}\right| Q_t^{AI} = \left|\widehat{\beta}^{\text{claim}}\right| H_t^{AI}\overline{N}. \tag{43}$$

AI was used by approximately 12,025 households in 2023, 23,286 households in 2024, and 24,504 households in 2025. The total number of AI-processed household-years during the main adoption period is therefore

$$H_{2023:2025}^{AI} = 12{,}025 + 23{,}286 + 24{,}504 = 59{,}815. \tag{44}$$

Using the sample mean of 16.78 insured cows per household gives

$$Q_{2023:2025}^{AI} = 59{,}815 \times 16.78 = 1{,}003{,}696 \tag{45}$$

AI-processed cow-years. Applying the estimated reduction in the claim rate gives

$$\Delta C_{2023:2025} = 0.007721 \times 1{,}003{,}696 \simeq 7{,}750. \tag{46}$$

Let $\overline{L}_t$ denote the indemnity per claimed cow in year t. The estimated reduction in claim payments is

$$V_{2023:2025}^{\text{claims}} = \sum_{t=2023}^{2025} \left|\widehat{\beta}^{\text{claim}}\right| H_t^{AI}\overline{NL}_t. \tag{47}$$

Using an indemnity of RMB 10,000 per cow in 2023 and RMB 8,000 per cow in 2024 and 2025 gives

$$V_{2023}^{\text{claims}} = 0.007721 \times 12{,}025 \times 16.78 \times 10{,}000 = \text{RMB } 15.58 \text{ million}, \tag{48}$$

$$V_{2024}^{\text{claims}} = 0.007721 \times 23{,}286 \times 16.78 \times 8{,}000 = \text{RMB } 24.14 \text{ million}, \tag{49}$$

$$V_{2025}^{\text{claims}} = 0.007721 \times 24{,}504 \times 16.78 \times 8{,}000 = \text{RMB } 25.40 \text{ million}. \tag{50}$$

The cumulative reduction in claim payments is therefore

$$V^{\text{claims}}_{2023:2025} = 15.58 + 24.14 + 25.40 = \text{RMB } 65.11 \text{ million}. \tag{51}$$

C.2 Expansion in Insurance Coverage

Let $N_{g,t}$ denote the number of underwriters who first adopted AI in year g, remained active in year t, and continued to use AI in year t. The observed cohort-year counts are

$$\begin{aligned} &N_{2023,2023} = 195, && N_{2023,2024} = 144, && N_{2023,2025} = 132, \\ &N_{2024,2024} = 141, && N_{2024,2025} = 87, && N_{2025,2025} = 85. \end{aligned} \tag{52}$$

For outcome $j \in \{H, Q\}$, where H denotes the number of households served and Q denotes the number of cows insured, let $\widehat{\beta}^{j}_{2023}$ denote the first-year effect and $\widehat{\beta}^{j}_{2024}$ denote the additional second-year effect. Because the estimated third-year coefficients are small and statistically insignificant, we impose

$$\widehat{\beta}^{j}_{2025} = 0, \tag{53}$$

so that the treatment effect plateaus after the second year.

Let θ^{j}_{s} denote the effect in the sth year since adoption. The implied dynamic treatment effect is

$$\theta^{j}_{s} = \begin{cases} \widehat{\beta}^{j}_{2023}, & s = 1, \\ \widehat{\beta}^{j}_{2023} + \widehat{\beta}^{j}_{2024}, & s \geq 2. \end{cases} \tag{54}$$

The aggregate effect in calendar year t is

$$\Delta Y^{j}_{t} = \sum_{g=2023}^{t} N_{g,t}\, \theta^{j}_{t-g+1}. \tag{55}$$

C.2.1 Additional Households

For households, the underwriter-level estimates are

$$\widehat{\beta}^{H}_{2023} = 16, \qquad \widehat{\beta}^{H}_{2024} = 18.4. \tag{56}$$

The implied effects are

$$\theta_1^H = 16, \qquad \theta_s^H = 16 + 18.4 = 34.4 \quad \text{for } s \geq 2. \tag{57}$$

The annual aggregate effects are

$$\Delta H_{2023} = 195 \times 16 = 3{,}120, \tag{58}$$
$$\Delta H_{2024} = 144 \times 34.4 + 141 \times 16 = 7{,}209.6, \tag{59}$$
$$\Delta H_{2025} = (132 + 87) \times 34.4 + 85 \times 16 = 8{,}893.6. \tag{60}$$

The cumulative increase in insured household-years is therefore

$$\Delta H_{2023:2025} = 3{,}120 + 7{,}209.6 + 8{,}893.6 = 19{,}223.2. \tag{61}$$

C.2.2 Additional Insured Cows

For insured cows, the underwriter-level estimates are

$$\widehat{\beta}_{2023}^{Q} = 413, \qquad \widehat{\beta}_{2024}^{Q} = 477. \tag{62}$$

The implied effects are

$$\theta_1^Q = 413, \qquad \theta_s^Q = 413 + 477 = 890 \quad \text{for } s \geq 2. \tag{63}$$

The annual aggregate effects are

$$\Delta Q_{2023} = 195 \times 413 = 80{,}535, \tag{64}$$
$$\Delta Q_{2024} = 144 \times 890 + 141 \times 413 = 186{,}393, \tag{65}$$
$$\Delta Q_{2025} = (132 + 87) \times 890 + 85 \times 413 = 230{,}015. \tag{66}$$

The cumulative increase in insured cow-years is therefore

$$\Delta Q_{2023:2025} = 80{,}535 + 186{,}393 + 230{,}015 = 496{,}943. \tag{67}$$

Appendix Table 1: AI Underwriting and Cow-Level Claim Rates in 2023

	Full sample			Subsample w. within HH variation
	(1) No controls	(2) Controls	(3) Controls + HH FE	(4) Controls + HH FE
AI	-0.0037***	-0.0026**	-0.0072*	-0.0125***
	(0.0011)	(0.0012)	(0.0041)	(0.0044)
Controls	No	Yes	Yes	Yes
Household FE	No	No	Yes	Yes
Observations	454,804	454,804	454,804	42,855
R-squared	0.000	0.001	0.102	0.074

Notes: This table reports cow-level regressions using the 2023 sample. The dependent variable is an indicator for whether the cow had a paid claim. *AI* is an indicator for whether the cow was processed using AI-based cattle facial recognition. Controls include premium per cow, household insured herd size, and an indicator for newly insured cows. Column (4) restricts the sample to households with within-household variation in AI use in 2023. Standard errors, clustered at the household level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2.3 Value of Additional Coverage

Let L_t denote the insured amount per cow in year t, with

$$L_{2023} = 10{,}000, \qquad L_{2024} = L_{2025} = 8{,}000. \tag{68}$$

The value of additional livestock brought under formal insurance is

$$\begin{aligned} V^{\text{coverage}} &= \sum_{t=2023}^{2025} \Delta Q_t L_t \\ &= 80{,}535 \times 10{,}000 + 186{,}393 \times 8{,}000 + 230{,}015 \times 8{,}000 \\ &= 4{,}136{,}614{,}000 \text{ yuan} \simeq \text{RMB } 4.14 \text{ billion}. \end{aligned} \tag{69}$$

At the statutory premium rate of $r = 0.06$, the associated additional premium volume is

$$V^{\text{premium}} = rV^{\text{coverage}} = 0.06 \times 4{,}136{,}614{,}000 = 248{,}196{,}840 \text{ yuan} \simeq \text{RMB } 248.2 \text{ million}. \tag{70}$$

Appendix Table 2: AI Exposure, Claim Rates, and Insured Herd Size

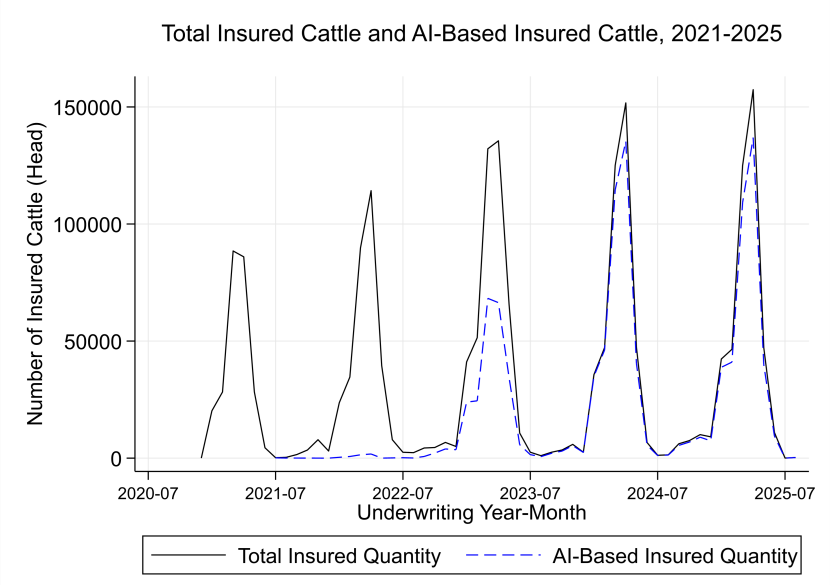
Year	Claim rate	Number of cows
2021	-0.000	0.256
	(0.004)	(0.266)
2023	-0.008**	0.811***
	(0.003)	(0.239)
2024	-0.004	-0.352
	(0.003)	(0.276)
2025	NA	-0.464*
		(0.278)
Observations	37459	49020
Household FE	Yes	Yes
Year FE	Yes	Yes

Notes: This table reports household-level event-study coefficients. The omitted year is 2022. Standard errors clustered by household are in parentheses. The claim-rate regression is estimated using 2021–2024, so the 2025 claim-rate coefficient is reported as NA. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D Additional Tables

E Appendix Figures

Appendix Figure 2: Number of Insured Cattle by Year-Month



Notes: This figure plots the quantity of insured cattle and the quantity of AI-Based insured cattle by year-month. Because of transhumance, the main insured cattle are tagging between March and April.