Artificial Intelligence (AI) and Agricultural Employment

Abstract

We quantify how artificial intelligence (AI) innovations affect U.S. agricultural employment. Using 2003–2023 U.S. Patent and Trademark Office records, we construct a measure of agriculture's exposure to AI by classifying AI patents and mapping them to subsectors through Cooperative Patent Classification (CPC) and North American Industry Classification System (NAICS) concordances. A shift–share design with an instrumental variable approach interacts national AI innovation trends with county-level lagged employment shares. Estimates indicate that AI exposure raises employment in crop production (NAICS 111) by 10.6% and in animal production (NAICS 112) by 6.8%, relative to mean employment levels in each subsector. Decomposing AI based on its underlying function reveals heterogeneity in employment effects. Execution-oriented AI (hardware and automation) reduces overall agricultural employment (NAICS 11) by 6.9%, while cognition-oriented AI (decision-support) and perception-oriented AI (sensing) increase employment (4.3% and 6%, respectively). These domain-specific patterns are consistent across crop and animal subsectors, with stronger employment effects in crop agriculture (-12.8% for execution-, 9.1% for cognition-, and 10% for perception-oriented AI) than in animal agriculture (-4.5% for execution-, and 7.8% for perception-oriented AI, respectively). Results show that AI does not uniformly displace farm labor; instead, its effects depend on technological complementarities and task reallocation. By uncovering domain-specific dynamics, this study demonstrates how targeted AI innovations can augment agricultural employment, informing policies that support skill upgrading and diffusion of complementary technologies.

Keywords: artificial intelligence; agricultural labor; patents; automation; task complementarity
JEL codes: Q16; J23; J43; O33.

1 Introduction

The rise of artificial intelligence (AI) has renewed attention to the interplay of technology, capital, and labor (Acemoglu et al., 2022; Brynjolfsson & McAfee, 2014; Furman & Seamans, 2019). In agriculture, optimism about AI's transformative potential is evident in recent calls from the National Institute of Food and Agriculture (NIFA) for advances in machine learning, autonomous systems, decision-support tools, and data visualization (U.S. National Science Foundation, 2021; USDA-NIFA, 2025). These prospects are especially salient in specialty crop farming, where labor-intensive tasks remain difficult to mechanize and automation has lagged behind other sectors (U.S. House Committee on Agriculture, 2023). Compared to manufacturing or services, agricultural production tasks are highly variable, context-dependent, and reliant on tacit knowledge, adaptive decision-making, and fine motor skills. Harvesting fruit, for example, requires workers to judge ripeness in real time, navigate uneven canopies, and balance efficiency with safety—tasks still resistant to mechanization. Such characteristics underscore both the promise of AI in augmenting agricultural work and the uncertainty of its labor-market consequences. AI may substitute for some tasks while complementing labor in others by raising productivity or creating new forms of work (Acemoglu & Johnson, 2023).[1] Consequently, the net effect of AI technologies on agricultural employment remains ambiguous and requires empirical investigation.

Structural shifts in the U.S. agricultural labor market further underscore the relevance of AI technologies. Producers and policymakers face growing concerns about declining labor availability and rising costs (Martin and Rutledge, 2024), driven by demographic transitions in migrant-sending regions (D. Charlton and Taylor, 2016), declining mobility of domestic workers (Fan et al., 2015), persistent shortages in key agricultural states (Hertz and Zahniser, 2013; Richards, 2018), and changing labor regulations such as state minimum wages

[1] In a survey of 2,000 firms across seven OECD countries, 66% of employers in manufacturing and 72% in finance report that AI has replaced tasks once performed by workers, but about half in each sector also report that AI has created new tasks (Lane et al., 2023).

and H-2A guest worker requirements (Castillo et al., 2024; Martin & Rutledge, 2022; Rutledge et al., 2025). These trends are particularly worrisome in the production of specialty crops, where labor expenses account for about 40% of total cash expenses in the industry (ERS, 2024), and employment represents about 52% of all U.S. agricultural workers (U.S. Bureau of Labor Statistics, 2025). While productivity gains and favorable output prices have partially offset rising labor costs in recent years (Hamilton et al., 2022; Shields, 2010), the sustainability of this balance remains uncertain. In this context, AI technologies are not only a potential source of productivity growth but may also be necessary to maintain output and competitiveness in labor-intensive sectors of U.S. agriculture.

This paper examines the effects of AI innovations on agricultural employment in the United States. A persistent challenge in this area is the lack of representative data on actual adoption or usage of AI-driven technologies (Frank et al., 2019; Raj and Seamans, 2019). To address this, we construct a novel measure of agriculture's exposure to AI innovations using patent records from 2003 to 2023, which we link to county-level employment and demographic data. Patents are widely used as a measure for emerging technologies not yet broadly deployed (Abood and Feltenberger, 2018; Tseng and Ting, 2013), and recent advances in natural language processing (NLP) allow more precise identification of AI-related inventions (Montobbio et al., 2022; Pairolero et al., 2025; Prato et al., 2019). We employ this measure within a shift–share framework similar to Acemoglu et al., 2020 and Mann and Püttmann, 2023, interacting local employment shares with national trends in AI patenting. Following Borusyak et al., 2022 and Goldsmith-Pinkham et al., 2020, our identification strategy exploits exogenous variation in local exposure to AI-driven innovation, supplemented with instruments based on foreign patent counts (Marguerit, 2025) and fixed effects for USDA-ERS rural commuting zones.

Our work contributes to the literature on technological change and agricultural labor markets. Recent studies document producers' adaptations to tightening farm labor supply in the United States (D. Charlton et al., 2019a; Win et al., 2025) and assess whether labor-saving technologies can mitigate production losses (Rutledge & Mérel, 2023). Using daily records from a large California strawberry farm, Hamilton et al. (2022) show that non-autonomous mechanized aids increase worker productivity by 5–6% but also find that labor-augmenting mechanization can dampen long-run capital investment and aggregate productivity under oligopsonistic labor markets. D. Charlton and Kostandini (2021) report that stricter immigration enforcement increased adoption of labor-saving technologies by U.S. dairies, yet efficiency gains did not fully offset losses from higher labor costs. We add to this literature by providing, to our knowledge, the first causal evidence on the labor-market effects of AI innovations in agriculture. Unlike prior work focused at the farm or single-industry level, we leverage advances in automated patent classification to document aggregate changes in agricultural AI innovation to estimate employment effects nationally.

More broadly, we contribute to the literature on AI and labor markets. Hampole et al. (2025) develop a model in which employment effects depend on both the mean and dispersion of task exposure to AI and show that higher mean exposure reduces an occupation's employment share, with offsets from within-occupation task reallocation and firm-level productivity growth. Acemoglu et al. (2022) document rapid growth in AI-related job postings and changing skill demands but find limited impacts on employment or wages. Using patent-based exposure measures, Gathmann et al. (2024) shows that AI exposure shifts low-skilled workers from abstract to routine tasks. Related studies on generative AI report sizable productivity gains, especially for lower-productivity workers (Brynjolfsson et al., 2025; Dell'Acqua et al., 2023; Eloundou et al., 2024; Noy and Zhang, 2023). We complement this work by focusing on U.S. agriculture—a sector characterized by relatively low automation, scarce labor, a high share of blue-collar jobs, and few routine tasks in crop production. These features suggest that the mechanisms through which AI technologies shape employment in agriculture may diverge substantially from those in office-based sectors.

Previewing our findings, we show that exposure to AI innovation increases employment in both crop production (NAICS 111) and animal production (NAICS 112), suggesting that AI complements hired farm labor and may generate productivity spillovers that offset substitution pressures. Consistent with a task-based view of technology, a functional-domain decomposition reveals pronounced heterogeneity based upon the type of underlying AI innovation; exposure to *execution-oriented AI* reduces employment, whereas exposure to *perception- and cognition-oriented AI* increases employment.

The remainder of the paper is organized as follows. Section 2 defines AI technologies in agriculture. Section 3 describes patent and county-level employment data. Section 4 outlines the empirical model and identification strategy. Sections 5 and 6 presents results and situates them within the existing literature. Section 7 concludes.

2 Defining AI in Agriculture

Artificial intelligence (AI) has become increasingly prominent in agricultural policy debates as a catchphrase, yet the term often lacks a clear definition, even as its potential is framed in relation to one of the sector's most persistent challenges—the dependence on costly or scarce human labor. Positioned as a remedy, AI is often described as capable of replicating certain human tasks and enhancing data-driven decision-making, with applications that may raise productivity, create new opportunities in AgTech, or displace existing jobs.

To advance policy discussions around labor market impacts constructively, AI should be defined not in abstract terms, but in ways directly relevant to agricultural contexts. AI refers to computational technologies designed to perform tasks that typically require human intelligence (National Institute of Standards and Technology, U.S. Department of Commerce, 2019).[2] With labor policy implications in mind, we adopt a broad view of AI in agriculture that extends beyond recent generative applications to encompass advances in sensing, data collection, decision support, and automation. Many of these innovations pre-

[2]We use the term AI to refer to artificial narrow intelligence (ANI). As of 2025, only ANI—applications designed for specific tasks—is operationally relevant, although the AI literature also distinguishes artificial general intelligence (AGI) and artificial superintelligence (ASI) (Wang et al., 2021).

date modern machine learning but serve as important precursors, and patent activity provides a useful measure of their cumulative development. Our analysis focuses on 2003–2023, a period when AI-related patents expanded sharply from a low base, enabled by advances in computing power, the miniaturization of sensors and processors, and data storage capacity (Radosavljevic & Kavalieros, 2022; Tantalaki et al., 2019).

Following Onel et al. (2025) and Wang et al. (2021), we classify AI innovations into three functional domains, each reflecting a core human capability. *Perception-oriented AI* refers to systems that interpret external data; *cognition and learning-oriented AI* refers to systems that learn from data to generate new knowledge; and *execution-oriented AI* refers to systems that apply knowledge through physical or digital action (Bruner and Postman, 1949; Kaplan and Haenlein, 2019; Onel et al., 2025; Wang et al., 2021). This taxonomy provides an analytical framework for distinguishing heterogeneous employment effects across different modalities of AI technologies.

Applications of AI in agriculture span all three domains. *Perception-oriented AI* includes machine vision for weed detection, where human perception often misjudges weed density (Andújar et al., 2010); ripeness estimation of specialty crops using non-destructive imaging (Vrochidou et al., 2021); and audio recognition for diagnosing livestock disease (Neethirajan, 2020; Sadeghi et al., 2023). *Cognition-oriented AI* builds on these data streams to provide decision support, such as optimization algorithms for path planning in autonomous machinery (Galceran and Carreras, 2013), soil and irrigation management using learning algorithms (Chen et al., 2022; Singh, 2014), or adaptive grazing strategies that integrate livestock habits and forage cycles. *Execution-oriented AI* encompasses the hardware that acts on such knowledge, including smart robotic aids that increase workers' harvesting speed (Fei and Vougioukas, 2021), crop-transport robots that reduce worker downtime (Peng et al., 2022), and robotic systems for sorting, grading, milking, or shearing (Oliveira et al., 2021). Taken together, these examples underscore that AI is not a single technology but a diverse set of innovations with heterogeneous implications for agricultural labor demand and policy design.

3 Data

Figure A.1 in Appendix A provides a schematic overview of how the empirical dataset is constructed. We begin with the universe of U.S. utility patents from PatentsView (2003–2023), which are mapped to agricultural subsectors through a two-stage classification procedure. Agricultural patents are then evaluated for AI content using the supervised ML model of Pairolero et al. (2025). Each AI patent is apportioned fractionally across three functional domains—Perception, Cognition and Learning, and Execution—so that the shares sum to one. These normalized domain contributions are aggregated at the subsector level and collapsed into three-year, non-overlapping "AI exposure shifts." The exposure measures are subsequently merged with county-level agricultural employment data from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW), together with farm income from the Bureau of Economic Analysis (BEA) and demographic controls from the National Center for Health Statistics (NCHS). The final dataset is a county–year panel spanning 2003-2005 to 2021-2023, with cross-sectional variation in local labor markets and time-series variation in AI exposure. Below we provide details of each data construction stage.

3.1 Patent Data

The primary data source for innovation is the universe of "utility patents"[3] granted by the USPTO between 2003 and 2023, accessed through PatentsView. The USPTO applies relatively broad patenting eligibility standards, which allows it to capture emerging and general-purpose technologies (e.g., digital agriculture, robotics, or biotech) that are economically

[3]Utility patents are defined as patents that include novel machines, processes, and compositions of matter.

significant but less consistently recorded in other patent systems. Utility patents comprise about 90% of all annual patent grants, compared to 8% for design patents and 2% for plant patents.[4] During the sample period, annual utility patent grants grew from about 150,000 to over 350,000. Patent records include grant date, assignee country, and Cooperative Patent Classification (CPC) tags, which provide standardized identifiers for technological domains. For example, the technology class "walking robots" in a patent is consistently coded under the CPC tag B62D57/032.

Linking Patents to Agriculture

We define agriculture using the North American Industry Classification System (NAICS). Specifically, we include subsectors 111 (Crop Production), 112 (Animal Production and Aquaculture), 113 (Forestry and Logging), and 114 (Fishing, Hunting, and Trapping). Supporting subsector 115 (Agricultural Services) is reconciled with its corresponding activity: 1151 with 111, 1152 with 112, and 1153 with 113. Production is considered complete at the "farm gate", the point of first market transaction. Defining production at the farm gate ensures that our measures are limited to primary agricultural activities and avoids conflating them with downstream sectors like food manufacturing or distribution.

We link patents to these agricultural subsectors using a two-step procedure. First, we classify patents as agricultural if their leading CPC tag appears on the list of agriculture-relevant codes used by Clancy et al. (2020). We then expand this list based on misclassifications detected during replication of the Goldschlag et al. (2020) concordance. For example, excluding domain-specific terms such as "milking" can result in animal husbandry patents being misplaced into non-agricultural industries. Similarly, several CPC codes tied to climate resilience and adaptation were introduced only after 2014 and are absent from the original concordance in Goldschlag et al. (2020), requiring explicit inclusion in agriculture-relevant

[4]Plant patents, established in 1930, protect asexually reproduced plant varieties as a distinct form of intellectual property. Nearly half of all plant patents belong only to two assignees (Clancy et al., 2020).

CPC tags. We include our expansion of the agriculture-relevant CPC tags in Supplementary Online Materials, Table S1.

Second, for patents not captured by the initial rule-based screening, we apply the probabilistic concordance developed by Goldschlag et al. (2020), updated through 2023. This concordance applies Bayesian updating to estimate the probability that each CPC code maps to a NAICS agricultural subindustry. We consider the full vector of CPC codes associated with each patent. We truncate CPC codes at four digits, collapse duplicates, and drop tags with zero posterior probability of relevance to agricultural sub-industries. For the remaining tags, we compute posterior means by sub-industry and assign a patent to agriculture if any agricultural sub-industry has a posterior probability above 0.5. This symmetric Bayesian decision rule is standard in probabilistic classification and we confirm robustness to alternative industrial thresholds (e.g., 0.6), which yield similar findings (Appendix B.1, Figures B.2a and B.2b).

Identifying AI Content and Functional AI Domains

To detect AI-related innovation, we draw on the concordance developed by Pairolero et al. (2025), which applies a supervised machine learning model trained on labeled patent data. The model assigns each patent a probability score across eight AI subdomains: Machine Learning, Evolutionary Computation, Natural Language Processing, Vision Recognition, Speech Recognition, Knowledge Representation, Planning and Control, and Hardware. We summarize these into a single AI likelihood per patent by taking the maximum probability score across the eight subdomains. Patents are then ranked by this maximum score, and those in the top 20% of the distribution are classified as AI patents, while the remainder are treated as non-AI. This thresholding rule provides a practical way to identify patents with sufficiently strong AI content. Appendix B.1, Figures B.1a and B.1b confirm that results are robust to more stringent percentile cutoffs. Figure 1 shows the evolution of AI innovation and non-AI innovations in agriculture over time.

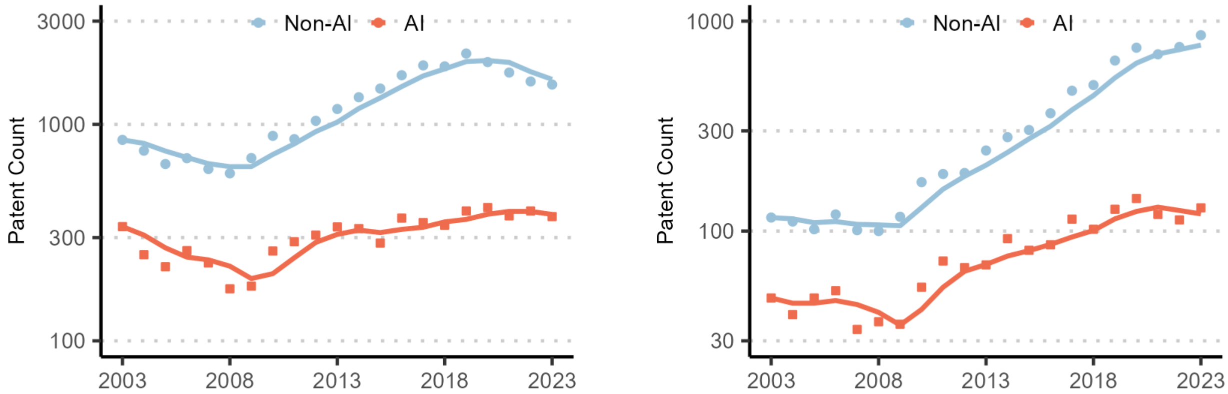
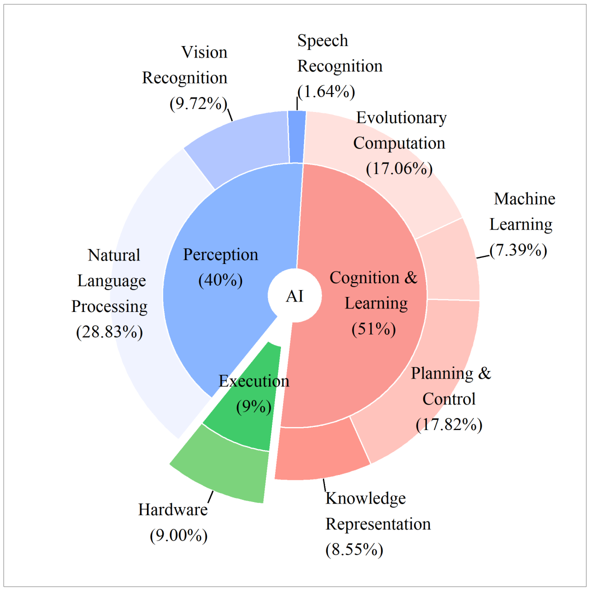


Figure 1. Historical trends of AI Innovation in Agriculture

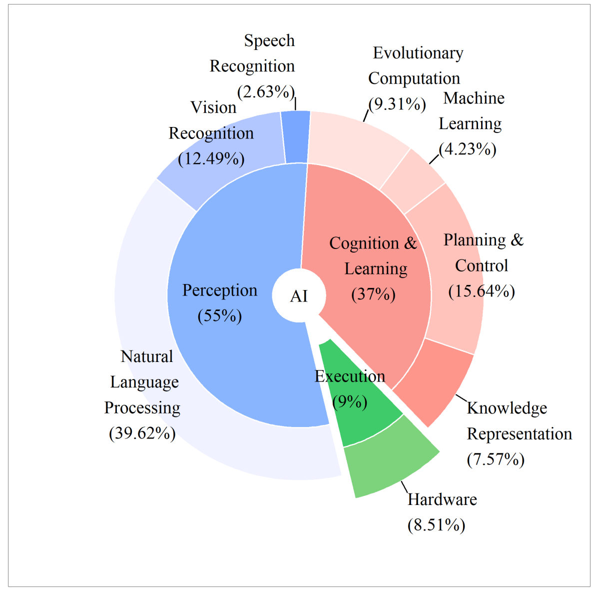
Source: Own elaboration using USPTO records and Pairolero et al., 2025. Solid lines are 3-year moving averages.

To provide a more interpretable characterization of AI technologies and ensure sufficient observations within each agricultural subsector, we group the eight AI subdomains into three broader functional domains that mirror three core human capabilities involved in the technology: (i) *Perception-oriented AI*, which captures technologies that sense or interpret input (NLP, Speech, Vision); (ii) *Cognition and Learning Oriented AI*, which captures technologies that learn, reason, or plan (Machine Learning, Evolutionary Computation, Knowledge Representation, Planning and Control); and (iii) *Execution-oriented AI*, which captures technologies that physically implement or operate (Hardware) (Kaplan & Haenlein, 2019; Onel et al., 2025; Wang et al., 2021). For each patent, we measure domain relevance as the maximum score across its associated subdomains.

Because patents often span more than one capability, we normalize these three functional domain scores to sum to one. Each AI patent is then apportioned fractionally across Perception, Cognition, and Execution in proportion to its relative strength. For instance, a patent with probability one in Perception, one in Cognition, and zero in Execution is assigned equally to Perception and Cognition (0.5 each), and not to Execution. This proportional allocation prevents double counting, produces compositional comparability across domains, and provides the basis for subsequent AI-exposure measures. Figure 2 illustrates the distribution of agricultural AI patents across functional domains for the 2003-2023 period.



(a) Crop Agriculture (NAICS 111).



(b) Animal Agriculture (NAICS 112).

Figure 2. Composition of AI Innovation in Agriculture.

Source: Own elaboration using USPTO records and Pairolero et al., 2025.

Constructing AI Intensity Measures

We tabulate patents by AI domains, agricultural subindustries, year granted, and assignee's location (United States, European countries, or other foreign origin). To account for large differences in patenting activity across industries, we transform patent counts using the natural logarithm of one plus the count, following Acemoglu et al. (2020) and Mann and Püttmann (2023). This transformation dampens the influence of very large patent numbers, reflecting the idea that the first few patents in a domain convey much more information about technological intensity than additional patents at the margin.

Because patents typically diffuse into production with a lag, and their labor market effects materialize only in the medium run (Brynjolfsson et al., 2019), we aggregate industry-specific AI patent flows over three-year periods. We treat patents as a flow of new inventive activity and use three-year sums to capture incremental additions that serve as the industry–time "shifts" in our design:

$$\text{Shift}_{j,t} = \sum_{\tau=t-2}^{t} \ln\bigl(1 + (\text{count of AI patents})_{j,\tau}\bigr) \tag{1}$$

where $j \in \{111, 112, 113, 114\}$ indexes agricultural subindustries and t denotes years. We compute three-year aggregates and anchor them to the non-overlapping years $t \in \{2005, 2008, 2011, 2014, 2017, 2020, 2023\}$. Consistent with the shift–share design in technology and labor market studies (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020), $\text{Shift}_{j,t}$ varies over time but not across space. It is best interpreted as a national industry–time AI innovation shock, or the common arrival of new AI patents relevant to industry j during period t. Local exposure to the new innovation arises only through interaction with counties' baseline employment shares. In other words, Equation (1) creates a time-varying measure of AI innovation shocks that apply equally nationwide but differentially affect local labor markets depending on their industry mix.

3.2 Economic and Demographic Data

We supplement the patent data with county-level measures of agricultural activity, labor, and demographics. Farm revenues and expenses (in logarithms) are drawn from the BEA, Farm Income and Expenses series. Demographic measures come from the NCHS Race-Bridged Population Estimates, including the working-age population (14–65) and shares of females, Hispanics, and residents under 65, which capture relevant dimensions of labor supply heterogeneity (Gallardo and Sauer, 2018; Mendola, 2008; Peterman et al., 2014).

Employment data are from the BLS-QCEW, covering NAICS agricultural subindustries 111–114 (Crop Production, Animal Production and Aquaculture, Forestry and Logging, Fishing, Hunting and Trapping, respectively.) We define the agricultural employment rate as the number of employees in these subsectors per 1,000 working-age residents in the county. Because QCEW is based on state unemployment insurance (SUI) records covering nearly all employers, it provides a highly representative measure of formal employment dynamics and minimizes self-reporting bias.

3.3 Addressing Data Limitations

A first limitation of the QCEW is the BLS disclosure policy. Employment and wage values for an industry–county–year cell are suppressed when the cell contains fewer than three establishments or when a single establishment accounts for at least 80 percent of employment. Suppression can occur even in relatively large cells, and the BLS applies a secondary "black-box" algorithm to prevent back-calculation from state totals. As a result, for a non-trivial share of 3-digit agricultural subindustry observations, the panel is unbalanced across counties and years. Because this unbalance is not random, it may introduce measurement error in the constructed AI exposure measures and could, in principle, bias estimates. Whereas prior studies drop suppressed observations (D. Charlton et al., 2019b; Rutledge et al., 2023), we adopt two strategies to recover and retain some of the missing information. First, when QCEW reports employment totals for a Metropolitan Statistical Area (MSA) alongside all but one of its constituent counties, we impute the supressed county value by subtracting observed county totals from the MSA total. Second, we collapse the data into three-year periods (triennia), which reduces suppression, smooths annual volatility, and aligns the data with our medium-run research design. After constructing the triennial panel, we drop any remaining observations with missing values and exclude outliers, defined as observations in the top or bottom one percent of the outcome distribution. Robustness checks that remove MSA imputations (Table B.2) and drop the ten most suppressed states (Table B.3) confirm that our results are not driven by these procedures.

A second limitation is that QCEW data cover only workers subject to State Unemployment Insurance (SUI). Because most states exempt farmers from paying SUI on H-2A guest workers–legal seasonal workers concentrated in crop agriculture and often employed through farm labor contractors–H-2A employment is largely excluded from the QCEW. Three states—California, Oregon, and Washington—are exceptions, since farmers there are required to report H-2A employment for SUI purposes. Given that H-2A workers represent 10–15 percent of the U.S. agricultural labor force, this partial exclusion raises concerns about comparability across states. To address this issue, we exclude employment from NAICS industry 115 ("Support Activities for Agriculture and Forestry"), which is disproportionately composed of NAICS 115115 ("Farm Labor Contractors and Crew Leaders") and is especially large in California, Oregon, and Washington. This subindustry is the most likely channel through which H-2A employment enters the QCEW in these states. Although excluding NAICS 115115 reduces measurement error and improves comparability, we also conduct robustness checks that reincorporate NAICS 115115 into crop labor and that restrict the sample to counties where this subindustry is observed (Table B.4).

After these adjustments, and excluding Alaska, Hawaii, and U.S. territories, our analysis uses an unbalanced panel of 1,643 counties observed over seven triennia: 2003–2005, 2006–2008, 2009–2011, 2012–2014, 2015–2017, 2018–2020, and 2021–2023. Table 1 provides summary statistics for the merged USPTO–QCEW data used in our analysis.

4 Empirical Framework

The objective is to estimate the causal effect of agricultural AI innovations on local farm employment. The outcome variable is the change in agricultural employment per 1,000 working-age residents at the county level. Treatment is defined using a shift–share measure of exposure to AI innovation, constructed by interacting national shifts in AI patenting with counties' pre-existing employment composition. This section introduces the shift-share

Table 1. Summary Statistics

	Mean	Standard Deviation			25th p.	Median	75th p.
		Overall	Between	Within			
Emp/Pop							
All Agriculture	16.56	25.87	27.21	4.58	2.68	7.23	19.57
Crop Agriculture	6.65	12.61	12.65	2.15	0.61	2.38	6.73
Animal Agriculture	9.01	19.71	21.13	3.66	0.28	2.18	8.26
Δ Emp/Pop							
All Agriculture	0.78	3.45	2.70	2.35	-0.36	0.12	1.17
Crop Agriculture	0.28	2.10	1.55	1.55	-0.14	0.01	0.48
Animal Agriculture	0.55	2.71	2.09	1.94	-0.08	0.00	0.46
Exposure to Technology							
Non-AI	16.85	3.15	3.27	0.81	16.12	17.46	18.63
All AI	12.36	3.80	3.87	1.34	11.08	13.08	14.72
Execution-oriented AI	7.38	2.79	2.73	1.31	6.14	7.42	9.25
Cognition-oriented AI	11.11	3.64	3.69	1.30	9.68	11.64	13.36
Perception-oriented AI	8.08	2.77	2.74	1.27	6.76	8.51	10.04
Other Variables							
Total Population	128.98	471.32	387.49	18.83	11.36	28.93	81.99
Working-age Population	85.85	322.16	263.37	11.73	7.00	18.61	53.03
Share of Females	0.50	0.02	0.02	0.00	0.49	0.50	0.51
Share of Hispanics	0.11	0.15	0.15	0.01	0.02	0.05	0.12
Share younger than 65	0.83	0.04	0.04	0.01	0.81	0.84	0.86
Farm Revenue	11.37	1.59	1.57	0.17	10.72	11.61	12.28
Farm Expenses	11.23	1.53	1.50	0.17	10.64	11.45	12.10

Notes: All Agriculture: NAICS 11; Crop Agriculture: NAICS:111; Animal Agriculture: NAICS 112.

variables used for estimation and outlines the rationale for establishing causal effects.

4.1 Shift-Share Design

We measure the potential adoption of AI technology using counties' exposure to AI innovations. Following Mann and Püttmann (2023) and Vargas (2011), we implement a shift–share design, treating exposure as the weighted average of industry-specific "shifts" in agricultural AI patenting activity. The shifts capture national increments in AI innovations by subindustry, while the weights are the county-level shares of hired workers across agricultural subindustries. County c's exposure to AI innovations in triennium t is therefore given by,

$$\Delta \mathbf{P}_{c,t} = \sum_{j=1}^{J} \text{Shift}_{j,t} \times \frac{L_{j,c,t-1}}{\sum_{j=1}^{J} L_{j,c,t-1}}, \tag{2}$$

where $\text{Shift}_{j,t}$ denotes the national arrival of new AI patents in agricultural subindustry j during t, and the weight is the lagged share of subindustry j in county c's total agricultural employment. Although new patents diffuse nationally, their local impact depends on the industry decomposition of employment. For example, a livestock-monitoring AI patent (e.g., Patent: 11564572 "Round-the-clock Monitoring of an Animal's Health Status") has greater relevance for counties specialized in animal production than for those with little animal industry employment.

We then estimate the effect of AI exposure on farm employment using the regression,

$$\Delta \left(\frac{L_{c,t}}{Pop_{c,t}} \right) = \beta_1 \Delta \mathbf{P}_{c,t} + \beta_2 \mathbf{X}_{c,t-1} + \eta_{z(c)} + \tau_t + \varepsilon_{c,t}, \tag{3}$$

where the dependent variable is the change in agricultural employment per 1,000 working-age residents between $t-1$ and t. [5] The right-hand side includes the shift–share treatment $\Delta \mathbf{P}_{c,t}$ and a vector of lagged controls $\mathbf{X}_{c,t-1}$ consisting of demographic shares (Hispanic, female, and over 65), the logarithms of farm income and farm expenses, and a shift–share measure of non-AI patents. The coefficient β_1 measures the average effect of exposure to AI patenting activity on local agricultural employment. The specification also includes commuting-zone fixed effects $\eta_{z(c)}$ to absorb persistent, time-invariant differences across local labor markets and period fixed effects τ_t to absorb shocks common to all counties in a given triennium.

Because workers search for jobs beyond their county of residence, wages and skill composition are spatially correlated within commuting zones (Hill et al., 2024). To account for this, we cluster standard errors by commuting zones defined by the USDA's Economic Research

[5] Taking first differences in the employment rate eliminates any time-invariant measurement error in the outcome. Although employment appears in both the outcome and the treatment, they are conceptually distinct: the outcome captures changes in the employment rate, while the treatment weights are based on lagged industry employment shares.

Service (Fowler, 2024). Clustering standard errors at the commuting-zone level allows for spatial correlation in unobserved shocks across counties within the same local labor market (Fowler, 2024; Fowler and Jensen, 2020).

To assess heterogeneity across types of AI, we decompose exposure to innovation into three functional AI domains–Perception, Cognition and Learning, and Execution–and estimate,

$$\Delta\left(\frac{L_{c,t}}{Pop_{c,t}}\right) = \gamma_1 \Delta\mathbf{P}^{P}_{c,t} + \gamma_2 \Delta\mathbf{P}^{C}_{c,t} + \gamma_3 \Delta\mathbf{P}^{E}_{c,t} + \gamma_4 \mathbf{X}_{c,t-1} + \eta_{z(c)} + \tau_t + \varepsilon_{c,t}, \tag{4}$$

where $\Delta\mathbf{P}^{P}_{c,t}$, $\Delta\mathbf{P}^{C}_{c,t}$, and $\Delta\mathbf{P}^{E}_{c,t}$ capture perception-, cognition-, and execution-oriented AI innovations, respectively. The parameters of interest, γ_1, γ_2, and γ_3, therefore indicate whether exposure to different domains of AI has distinct implications for agricultural labor demand. Regressions 3 and 4 are estimated using ordinary least squares (OLS) and two-stage least squares (2SLS), with instruments described in the next section.

4.2 Identification Strategy

The coefficients of interest $(\beta_1, \gamma_1, \gamma_2, \gamma_3)$ should represent a causal relationship from treatment to outcome, identifying causal effects of AI innovation shocks on local employment.

Following Adão et al. (2019), Borusyak et al. (2022), Christian and Barrett (2024), and Goldsmith-Pinkham et al. (2020), a shift–share variable is exogenous if either the "shifts" (i.e., national patent flows) or the "shares""(i.e., local employment composition) are exogenous. We address potential endogeneity in both components, focusing on reverse causality, omitted variables, and measurement error.

A first concern is reverse causality. Employment changes could, in principle, influence local employment composition. To limit this channel, we define the dependent variable as the first difference of the employment rate rather than its level, and we weight shifts using lagged rather than contemporaneous employment shares (Mann & Püttmann, 2023). It is therefore unlikely that local employment dynamics drive the treatment variable. Reverse causality running from local employment to national patenting—e.g., directed innovation—is also implausible, since no single county is large enough to affect national patenting trends.

A second concern is omitted variables. We include commuting-zone fixed effects to absorb persistent differences across local labor markets and period fixed effects to absorb aggregate shocks. In addition, we control for non-AI agricultural patenting, demographics (shares Hispanic, female, and over 65), and farm revenues and expenses. These steps reduce the scope for confounding local shocks.

A third concern is measurement error, arising from suppressed QCEW cells in some county–industry observations. As discussed in Section 3.3, we address this by imputing missing values where possible, aggregating to triennia, and excluding outliers. We also verify robustness of estimation results by dropping the top ten states most affected by suppression (Appendix B.2, Table B.3).

Finally, we acknowledge that patent endogeneity may arise if innovations filed by U.S. inventors respond directly to domestic agricultural industry conditions. To address this, we implement an instrumental variables strategy. Specifically, we construct shift–share instruments analogous to those in Equation (2) using only patents assigned to foreign inventors from European Union and the rest of the world. Foreign innovation affects U.S. innovation through diffusion, collaboration, citations, and possibly reverse engineering. Foreign inventors most likely respond to the economic conditions in their home countries and, therefore, their innovation is less correlated with employment trends in U.S. farms.

Together, these strategies mitigate the main sources of endogeneity and support a causal interpretation of the estimated coefficients in Equations (3) and (4).

5 Empirical Findings

Regressions are estimated separately for overall agricultural employment, crop production, and animal production subsectors. Baseline results, reported in Table 2, compare the effects of AI and non-AI exposure on changes in county-level employment shares. Next, we decompose the effect of AI into its three functional domains—perception-, cognition-, and execution-oriented AI—with results reported in Table 3. Finally, we present robustness checks, including specifications with state- rather than commuting-zone fixed effects, alternative thresholds for apportioning AI and agricultural patents, restrictions to states with minimal QCEW suppression, and a focus on H-2A–dominant counties. These results are reported in Appendix B.

5.1 Baseline Impact of Exposure to AI Innovation on Agricultural Employment

Table 2 reports the baseline estimates of how exposure to AI-related and non-AI innovations affects local agricultural employment. For the pooled "All Agriculture" sector, the OLS coefficient on AI exposure indicates a positive association with local agricultural employment, while the IV estimate (column 2) is similar in magnitude but no longer statistically significant at the 10% level. The subsector estimates, on the other hand, are larger in magnitude and more precisely estimated, providing evidence that AI innovations exert positive effects on agricultural labor demand.

In crop agriculture, the IV estimate for AI exposure is 0.528 p.p.[6] This implies that a one-standard-deviation[7] increase in AI exposure raises employment by $0.528 \times 1.34 = 0.71$ workers per 1,000 working-age individuals. Given the average crop employment share of 6.65

[6]'p.p.' stands for percentage point and refers to the arithmetic difference between two percentages.

[7]We use the *within* value reported in Table 1. The within standard deviation is calculated by measuring how far each observation departs from its county mean and then pooling this variation across all counties. This approach removes variation arising from persistent cross-county differences.

per $1,000$ reported in Table 1, this corresponds to a 10.6% increase ($0.71/6.65 \times 100\% = 10.6\%$) relative to the mean employment in the crop sector. In animal production, the pattern is similar. The IV coefficient for AI exposure is 0.456 p.p., which implies that a one–standard deviation increase in AI exposure raises employment by $0.456 \times 1.34 = 0.61$ workers per 1,000 working-age individuals. Relative to the sectoral average of 9.01 workers per 1,000, this corresponds to an employment increase of 6.8%.

By contrast, non-AI innovations tend to reduce agricultural employment, with negative and often statistically significant coefficients across all specifications. The IV estimate for non-AI exposure in crop agriculture is –0.603 p.p., translating into a reduction of $0.603 \times 0.81 = 0.49$ workers per $1,000$ people, or a 7.3% decline in employment relative to the crop sector mean. In animal agriculture, the IV coefficient for non-AI exposure is -0.503 p.p., indicating a decline of $0.503 \times 0.81 = 0.41$ workers per 1,000, or a 4.5% reduction relative to the sectoral mean.

These results indicate that, under the identifying assumptions of the shift–share IV design, exposure to AI innovation increases employment in both crop and animal agriculture, while non-AI innovations reduce employment by comparable magnitudes. The effect sizes are benchmarked using the within-county standard deviation of exposure (Table 1), which provides a conservative scale that removes persistent cross-county differences.

Comparing OLS and IV estimates also provides insight into potential biases in the OLS results. In crop agriculture, OLS coefficients have the same sign as the IV estimates but are smaller in magnitude. This pattern is consistent with attenuation bias arising from reverse causality, possibly through directed innovation in response to local labor market conditions, and underscores the value of using foreign patenting activity as an exogenous source of variation in U.S. domestic innovation. In animal agriculture, by contrast, the OLS and IV estimates are similar in both sign and magnitude, suggesting that reverse-causality concerns are less pronounced in this subsector, likely because animal agriculture is less subject to the

Table 2. Effects of Exposure to AI and Non-AI Innovation on Agricultural Employment, by Subsector (OLS and IV Estimates)

	Employment Rate in All Agriculture		Employment Rate in Crop Production		Employment Rate in Animal Production	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Non-AI innovation	-0.559***	-0.395	-0.191**	-0.603***	-0.503***	-0.505**
	(0.196)	(0.310)	(0.076)	(0.154)	(0.154)	(0.214)
AI innovation	0.548***	0.394	0.165**	0.528***	0.454***	0.456**
	(0.174)	(0.276)	(0.067)	(0.136)	(0.138)	(0.191)
FE by Year	X	X	X	X	X	X
FE by CZ	X	X	X	X	X	X
Num. Obs.	4626	4626	4626	4626	4626	4626
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		534.946		544.119		531.120
KP Wald F-stat		195.043		196.527		192.002

Notes: Robust standard errors clustered at the commuting-zone level are reported in parentheses. ***p ¡ 0.01, **p ¡ 0.05, *p ¡ 0.10. The dependent variable is the change in the number of employees in the respective subsector per 1,000 working-age individuals. The independent variables are changes in exposure to AI and non-AI innovations, constructed using shift–share measures. Each shift is defined by patents in the top 20% of agriculture probability and, for AI, also in the top 20% of AI probability. The first-stage Cragg–Donald Wald F-statistic and Kleibergen–Paap Wald F-statistic both exceed the Stock–Yogo critical values.

seasonal dynamics that shape innovation and employment in crop production.

5.2 Heterogeneous Effects by Functional Domains of AI Innovation

Table 3 shows that disaggregating AI into functional domains reveals striking heterogeneity in labor-market impacts. The coefficient on execution-oriented AI is consistently negative and statistically significant, consistent with machine–labor substitution. The IV estimate for the aggregate agricultural sector is -0.866 p.p., implying that a one–standard deviation increase in exposure to execution-oriented AI innovation reduces employment by 6.9% relative to the average agricultural employment rate. This effect reflects a sharper decline in crop agriculture (-0.650 p.p. $\times$ 1.31 / 6.65 $\times$ 100 = -12.8%) and a more moderate decline in animal agriculture (-0.312 p.p. $\times$ 1.31 / 9.01 $\times$ 100 = -4.5%), relative to the sectoral means.

Table 3. Effects of AI Exposure by Functional Domains on Agricultural Employment, by Subsector (OLS and IV Estimates)

	Employment Rate in All Agriculture		Employment Rate in Crop Production		Employment Rate in Animal Production	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Non-AI innovation	-0.370*	-0.349	-0.111	-0.404***	-0.444***	-0.337**
	(0.197)	(0.251)	(0.075)	(0.105)	(0.149)	(0.167)
Execution-AI innovation	-1.005***	-0.866***	-0.388***	-0.650***	-0.583***	-0.312*
	(0.211)	(0.281)	(0.104)	(0.142)	(0.142)	(0.177)
Cognition-AI innovation	0.421**	0.452*	0.114	0.464***	0.350**	0.166
	(0.187)	(0.262)	(0.076)	(0.122)	(0.140)	(0.179)
Perception-AI innovation	1.004***	0.778***	0.380***	0.524***	0.706***	0.554***
	(0.206)	(0.227)	(0.090)	(0.097)	(0.155)	(0.148)
FE by Year	X	X	X	X	X	X
FE by CZ	X	X	X	X	X	X
Num. Obs.	4626	4626	4626	4626	4626	4626
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		285.886		281.861		287.132
KP Wald F-stat		63.079		61.185		63.477

Notes: Robust standard errors clustered at the commuting-zone level are reported in parentheses. ***p ¡ 0.01, **p ¡ 0.05, *p ¡ 0.10. The dependent variable is the change in the number of employees in the respective subsector per 1,000 working-age individuals. The independent variables are changes in exposure to respective AI and non-AI innovations, constructed using shift–share measures. Each shift is defined by patents in the top 20% of agriculture probability and, for AI, also in the top 20% of AI probability. The first-stage Cragg–Donald Wald F-statistic and Kleibergen–Paap Wald F-statistic both exceed the Stock–Yogo critical values.

By contrast, cognition- and perception-oriented AI exposures show consistently positive coefficients. In the aggregate agricultural sector, a one–standard deviation increase in exposure to cognition-oriented AI raises employment by about 4.3%, while perception-oriented AI raises it by about 6%. In crop agriculture, the IV coefficient for cognition-oriented AI is 0.464 p.p., corresponding to a 9.1% increase in employment, and the coefficient for perception-oriented AI is 0.524 p.p., corresponding to a 10.0% increase in employment. In animal agriculture, the estimate for cognition-oriented AI is statistically insignificant, while that for perception-oriented AI remains positive and significant. A one–standard deviation increase in perception-oriented AI exposure raises employment in animal agriculture by 0.554 p.p. $\times$ 1.27 = 0.7 workers per 1,000, or about 7.8% relative to the sectoral mean.

Overall, the domain-specific patterns are consistent across crop and animal subsectors of agriculture, but the effects are larger and more precisely estimated in crop production. These results reinforce the interpretation that execution-oriented AI technologies substitute for labor, whereas perception- and cognition-oriented AI technologies complement and expand labor demand.

5.3 Robustness Checks

We assess the sensitivity of our findings to (i) alternative model specifications, including state fixed effects and alternative cutoffs for classifying AI and agricultural patents; (ii) suppression in the QCEW data; and (iii) partial coverage of H–2A employment in the QCEW. Numerical results are reported in Appendix B. Across these robustness checks, the magnitude and significance of the main coefficients remain stable, indicating that our conclusions are not driven by modeling choices or data construction decisions.

Sensitivity to Alternative Specifications. We first re-estimate the baseline and domain-disaggregated specifications using state fixed effects instead of commuting–zone fixed effects, clustering in both cases at the commuting–zone level. Coefficients are similar in sign and slightly larger in magnitude, with tighter confidence intervals. A one–standard deviation increase in exposure to AI raises employment by 4.1% in all agriculture, by 11.5% in crop Production, and by 8.5% in animal production (Table B.1).

We also probe the robustness of our patent classification. Holding the agricultural relevance cutoff at 50%, we progressively tighten the AI-content threshold from the top 20% to the top 10% of the AI-score distribution. Figures B.1a and B.1b plot point estimates and 90% confidence intervals for crop and animal production; the leftmost bars replicate the baseline threshold used in Table 2. We then raise the agricultural relevance cutoff from 50% to 60% and repeat the exercise (Figures B.2a–B.2b). In all cases, estimates retain their sign and become modestly smaller and more precisely estimated as thresholds are tightened.

Sensitivity to Suppression in QCEW Data. QCEW cell suppression can induce missingness that is plausibly nonrandom (see, Section 3.3 for details). We implement two checks. *(i) No imputation of supressed QCEW counties from MSA totals.* Our baseline back-calculates a suppressed county value when MSA totals and all but one county within the MSA are observed. Dropping this back-calculation reduces the sample by roughly 10% (from 4,626 to 4,290 observations). Results are virtually unchanged: a one–standard deviation increase in AI exposure raises employment by 10.6% in crop agriculture, and 8.2% in animal agriculture. Domain specific patterns mirror the baseline estimates as well, with execution-oriented AI maintaining negative and cognition- and perception-oriented AI inducing positive impacts on employment (Table B.2).

(ii) Trimming highly suppressed states. Prior studies such as D. Charlton et al. (2019b) and Rutledge et al. (2023) simply drop suppressed observations, while D. E. Charlton et al. (2025) address suppression by reconciling inconsistencies between county- and state-level aggregates. Their approach distributes the difference between state totals and summed county totals evenly across suppressed counties. While this method ensures internal consistency, it rests on the strong assumption that missing employment is uniformly distributed. We adopt a more conservative strategy that avoids introducing potential imputation bias. Specifically, we identify the states with the highest incidence of county-level suppression and exclude the top ten[8] from our analysis. This trimming approach prioritizes data integrity by retaining only states with more complete reporting. Although this reduces geographic coverage, it enhances the reliability of exposure measures by avoiding distributional assumptions. Point estimates from this trimmed sample are presented in Panel A of Table B.3 and are similar to those from the full sample in Table 2, though statistical significance is weaker outside the crop sector, in which a 13.3% change in employment is observed for a one-standard devi-

[8] District of Columbia, Rhode Island, Delaware, Nevada, Wyoming, Connecticut, Massachusetts, California, Pennsylvania, and Oklahoma.

ation increase in AI exposure. When disaggregating AI by functional domain in Panel B. of (Table B.3), the signs and relative magnitudes reproduce the baseline conclusions with slightly larger coefficients relative to those in Table 3.

Sensitivity to Partial Coverage of H–2A Employment in QCEW Data. Because most states exclude H–2A workers from SUI reporting, we omit NAICS 115 in the baseline to enhance cross-state comparability (see, Section 3.3 for details). In Table B.4, we reintegrate NAICS 115115 (Farm Labor Contractors and Crew Leaders) into crop employment and, separately, restrict the sample to counties with positive 115115 employment. In both cases, the main results are robust; the overall AI coefficient remains positive in crop agriculture, execution-oriented AI remains negative, and cognition- and perception-oriented AI remain positive (Table B.4, Panel B).

Taken together, these checks show that our central findings—overall AI exposure raises agricultural employment, with substitution concentrated in execution-oriented AI and complementarity in cognition- and perception-oriented AI—are insensitive to model specifications, suppression in QCEW data, and partial coverage of H–2A employment.

6 Discussion

When analyzed by functional domains, the effects of AI on farm employment follow a task-based pattern. Execution-oriented AI reduces employment, most likely through direct substitution, whereas perception- and cognition-oriented AI increase employment by raising the marginal productivity of labor in remaining tasks.

Execution-oriented AI is hardware-intensive, automating movement, machinery, and end-effectors. Employment declines in this domain likely reflect substitution in tasks where machines hold a clear comparative advantage. For example, smart milking machines, barn cleaners, and weeding machines can substitute for human workers directly by overtaking these tasks fully. This is consistent with earlier studies showing that automation reduces labor demand. Graetz and Michaels (2018) document negative employment effects of industrial robots; Acemoglu and Restrepo (2019) show that U.S. commuting zones more exposed to automation experienced slower job growth; de Souza and Li (2023) find sizable declines in low-skill operational employment in Brazil; and Hampole et al. (2025) provide recent firm-level evidence that AI substitutes for labor in exposed industries.

By contrast, perception- and cognition-oriented AI are associated with employment gains that reflect labor-augmenting complementarities. Hill et al. (2025) argue that farm automation often restructures task bundles rather than eliminating jobs, and our findings support this view. Complementarities are most evident in labor-intensive crops. Technologies such as real-time crop monitoring, variable nutrient application, and targeted pest control improve yield and quality by reducing crop losses and increasing the share of produce meeting premium grades. Similarly, cognition-oriented applications, such as decision support systems for harvest scheduling and logistics, enhance coordination and allow farms to stagger harvests or bring more produce to market over time. Together, these innovations expand per-acre workloads and increase labor demand to meet higher production and revenue targets.

AI can also reallocate labor within farms. For instance, autonomous strawberry harvest aids (Peng et al., 2022) reduce time spent on fruit transport, allowing workers to concentrate on the more productive picking task. Such division of labor enables workers to shift from lower-value tasks such as scouting, transport, or on-site grading toward higher-value, incentive-based activities like harvesting, as also emphasized by Hampole et al. (2025). These reallocations improve productivity, working conditions, and ergonomics, which can help sustain employment opportunities for an aging domestic farm workforce.

This task-based interpretation aligns with the "jagged technological frontier" of Dell'Acqua et al. (2023), which suggests that partial automation–where some tasks are fully mechanized while others remain human-dependent–can accelerate overall production and raise labor demand in complementary tasks. In agriculture, widespread displacement from AI productivity gains is unlikely. Seasonal and piece-rate payment schemes already incentivize workers to operate at full capacity, so higher productivity typically results in greater output rather than reduced employment. Evidence in other sectors supports this intensive-margin mechanism. Jiang et al. (2025) find that AI exposure increases hours worked and reduces leisure in competitive labor markets; Marguerit (2025) show that augmentation-oriented AI raises wages and the returns to skills; and Mäkelä and Stephany (2025) document that rising AI demand increases the value of complementary human skills such as resilience and analytical reasoning.

Taken together, these findings suggest that AI in agriculture primarily reshapes task allocation rather than eliminating work. Execution-oriented AI substitutes for labor in narrowly defined mechanical tasks, while perception- and cognition-oriented AI augment human input, expand workloads, and spread employment needs more evenly across time. Policy should therefore focus on facilitating task reallocation and skill upgrading in agricultural labor markets. Investments in technical training, certification for AI-assisted machinery, and support for seasonal labor mobility can help ensure that the productivity gains from partial automation translate into local employment and income growth.

7 Conclusion

There is much excitement and apprehension about the effects of AI on labor markets. This study contributes to the debate by focusing on agriculture, a sector that has long grappled with labor shortages alongside rising global demand for food. We extend the analysis of AI beyond generative applications to investigate multiple functional domains of AI, providing the first empirical study to use a shift–share design to estimate the causal impact of AI exposure on agricultural employment. Our measure of AI innovation is based on patents registered from 2003 to 2023, classified by functional domain of the underlying technology and apportioned by industry, then linked with county-level employment data across the continental United States.

We find that a one–standard deviation increase in overall AI exposure raises employment in crop farming by 0.528 p.p. (about 0.7 additional workers per 1,000 working-age individuals), equivalent to 10.6% increase relative to the sectoral employment mean, and in animal farming by 0.456 p.p., equivalent to 6.8% growth. Disaggregating AI into functional domains reveals substantial heterogeneity. Execution-oriented AI reduces employment, consistent with machine substitution, while perception- and cognition-oriented AI increase employment, consistent with productivity-enhancing complementarities. At the aggregate farm level (NAICS 11), a one–standard deviation increase in exposure to execution-oriented AI is associated with a 6.9% decline in employment, whereas comparable increases in exposure to cognition- and perception-oriented AI raise employment by 4.3% and 6.0%, respectively, relative to average agricultural employment per 1,000 individuals in a county. Results are similar across subsectors, though effects are more pronounced in crop agriculture than in animal agriculture.

Our study has strengths and limitations. Measuring AI innovation through automated text classification of patents inevitably introduces imprecision, and it assumes that patents are a reasonable proxy for usable technological advances or adoption. In addition, adoption of technology may vary across farms. Large commercial farms—responsible for 80 percent of output and most hired labor (Martin, 2021)—are more likely to invest early in AI-enabled equipment, while smaller farms may access technologies later through contracting. Aggregate estimates therefore mask heterogeneity in firm-level adoption, as early adopters could reshape local labor demand in ways that differ from the overall effect on commuting-zone labor markets. Nonetheless, the approach allows us to track the AI frontier at fine industry and geographic scales, capturing innovations as they emerge.

The findings bear directly on policy debates over agricultural labor shortages and food security. Contrary to concerns that AI uniformly displaces labor, our results suggest that perception- and cognition-oriented applications can alleviate labor access issues by augmenting rather than replacing farm tasks. In the crop sector, for example, these technologies improve field monitoring, harvest scheduling, and post-harvest handling. By reducing losses and smoothing the timing of harvest activities, they increase labor productivity and reduce idle periods within the season. Productivity gains can enable farms to expand planted acreage, indirectly increasing demand for seasonal workers. Public R&D and extension services can help realize these complementarities by promoting feasible and cost-effective innovations that enhance worker productivity and safety. In addition, investments in training, certification, and labor mobility programs could help ensure that productivity gains translate into higher local employment and incomes.

The link between farm labor and food output is also critical for food security. Rutledge and Mérel (2023) show that a 10% decline in labor supply reduces output of hand-harvested crops by 4.2%. Taking this as a reference, our estimates imply that adoption of perception- and cognition-oriented AI could sustain or expand output by bolstering employment during peak production periods.

Overall, the results highlight that AI in agriculture primarily reshapes task allocation rather than eliminating work altogether. Execution-oriented AI substitutes for labor in tasks where machines hold a clear advantage, but perception- and cognition-oriented AI augment labor in ways that can sustain or even expand employment. Recognizing this heterogeneity is essential for understanding AI's net effects and designing policies that ensure technological change strengthens both rural livelihoods and food security.

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Appendix

A Overview of the Data Construction Process

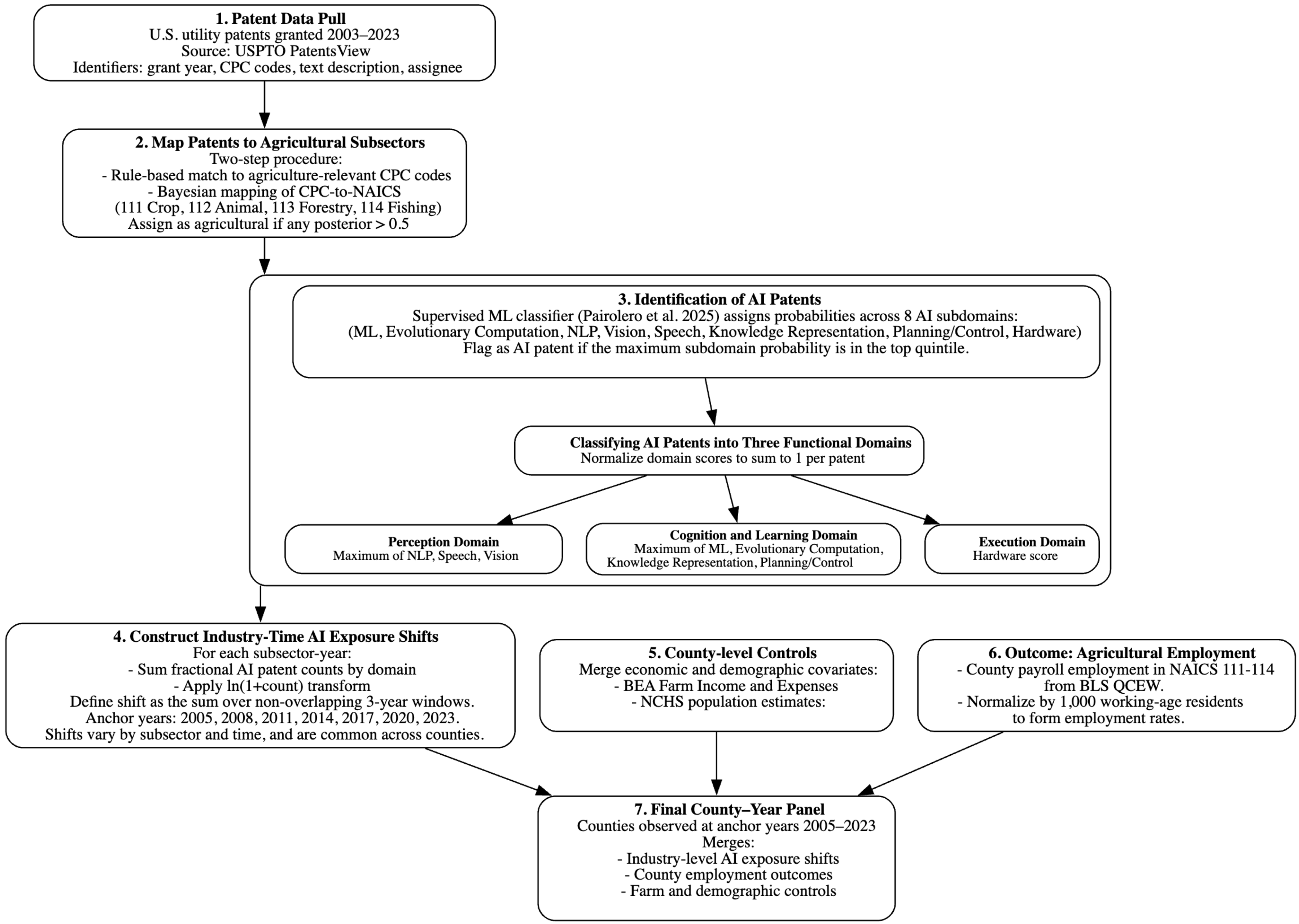


Figure A.1. Overview of the data construction process. The figure illustrates the sequential steps linking patent records to county-level labor market outcomes.

B Robustness Checks

B.1 Sensitivity to Alternative Specifications

Table B.1. AI exposure and county-level farm employment: State fixed effects

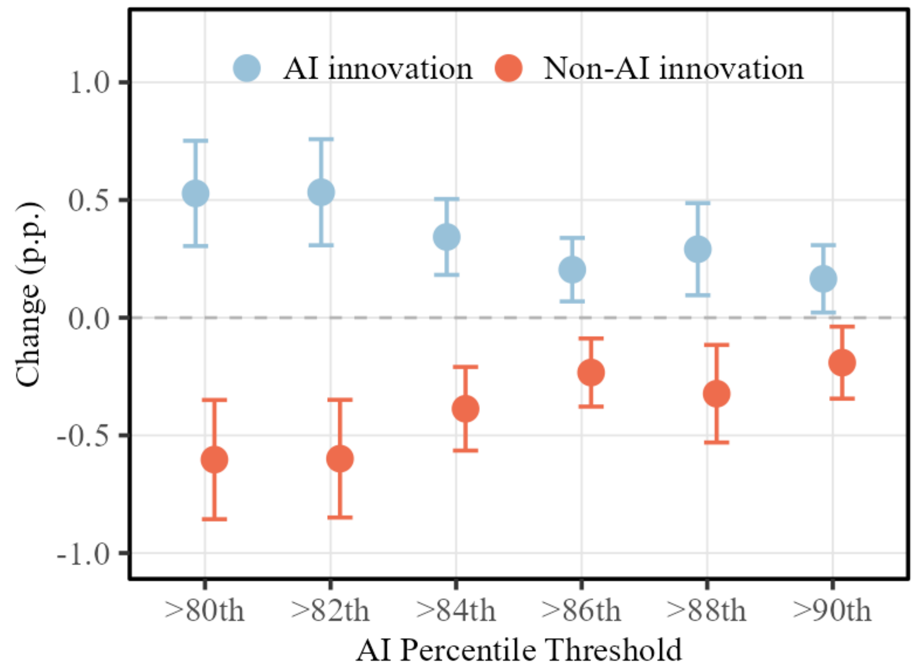
Panel A: Overall AI Innovation

	Employment Rate in All Agriculture		Employment Rate in Crop Production		Employment Rate in Animal Production	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Non-AI innovation	-0.665***	-0.552*	-0.213***	-0.634***	-0.604***	-0.662***
	(0.189)	(0.297)	(0.070)	(0.138)	(0.149)	(0.211)
AI innovation	0.616***	0.509*	0.196***	0.569***	0.525***	0.574***
	(0.167)	(0.263)	(0.061)	(0.122)	(0.132)	(0.187)
FE by Year	X	X	X	X	X	X
FE by State	X	X	X	X	X	X
Num.Obs.	4626	4626	4626	4626	4626	4626
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		649.365		656.625		644.244
KP Wald F-stat		283.428		284.502		280.933

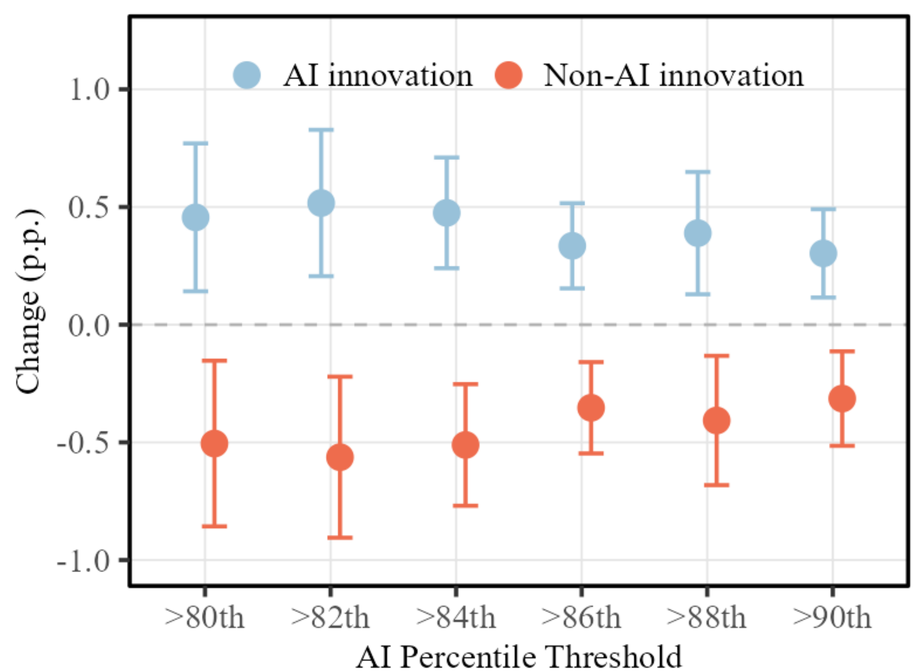
Panel B: AI Innovations by Functional Domains

	Employment Rate in All Agriculture		Employment Rate in Crop Production		Employment Rate in Animal Production	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Non-AI innovation	-0.246	-0.198	-0.133*	-0.448***	-0.336**	-0.235
	(0.183)	(0.234)	(0.070)	(0.099)	(0.136)	(0.151)
Execution-AI innovation	-1.084***	-1.050***	-0.354***	-0.646***	-0.698***	-0.509***
	(0.201)	(0.274)	(0.096)	(0.136)	(0.132)	(0.168)
Cognition-AI innovation	0.250	0.272	0.130*	0.494***	0.206	0.059
	(0.182)	(0.249)	(0.072)	(0.112)	(0.128)	(0.167)
Perception-AI innovation	1.124***	0.987***	0.363***	0.551***	0.859***	0.746***
	(0.191)	(0.219)	(0.084)	(0.096)	(0.145)	(0.137)
FE by Year	X	X	X	X	X	X
FE by State	X	X	X	X	X	X
Num.Obs.	4626	4626	4626	4626	4626	4626
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		278.043		275.631		279.001
KP Wald F-stat		49.801		49.127		50.136

Notes: Robust standard errors clustered at the commuting-zone level are reported in parentheses. ***p ¡ 0.01, **p ¡ 0.05, *p ¡ 0.10. The dependent variable is the change in the number of employees in the respective subsector per 1,000 working-age individuals. The independent variables are changes in exposure to AI and non-AI innovations, constructed using shift–share measures. The first-stage Cragg–Donald Wald F-statistic and Kleibergen–Paap Wald F-statistic both exceed the Stock–Yogo critical values.

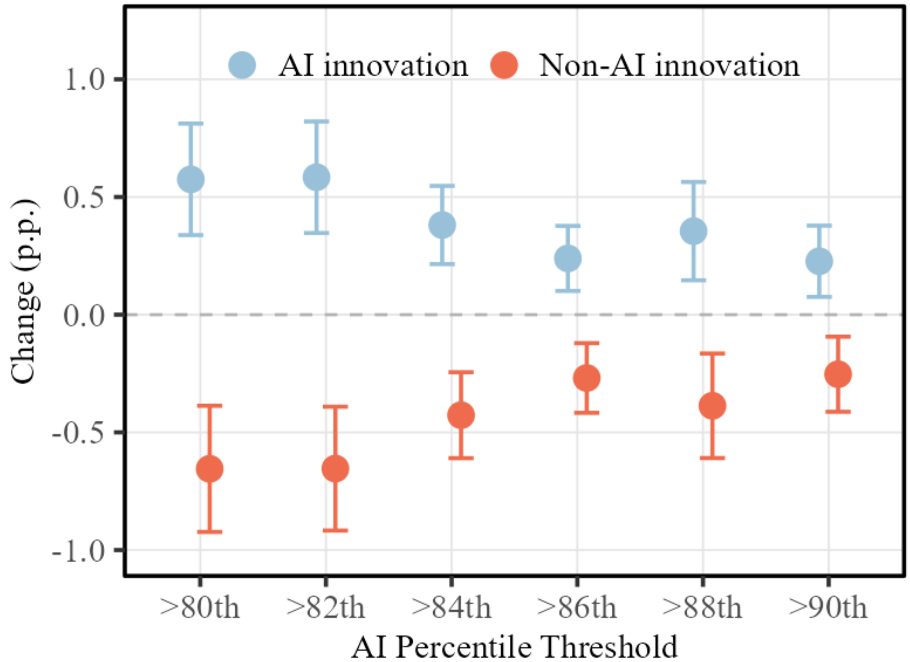


(a) Estimated Employment Effects in Crop Production (NAICS 111).

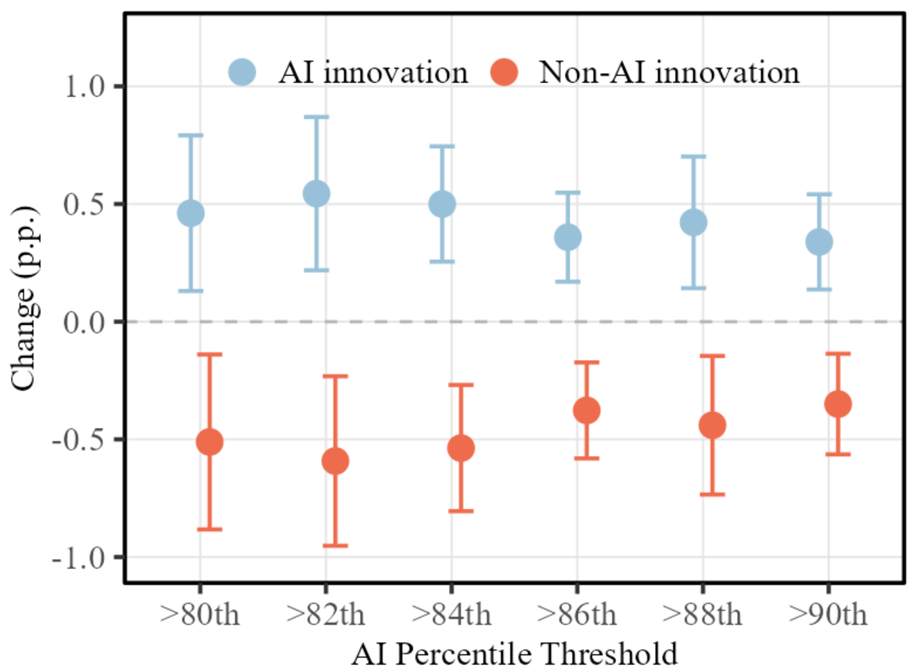


(b) Estimated Employment Effects in Animal Production (NAICS 112).

Figure B.1. Sensitivity of Estimated Employment Effects to AI Content Thresholds (Sectoral threshold for agriculture is kept at $\geq 50\%$).



(a) Estimated Employment Effects in Crop Production (NAICS 111).



(b) Estimated Employment Effects in Animal Production (NAICS 112).

Figure B.2. Sensitivity of Estimated Employment Effects to Sectoral Relevance Threshold (Probability of Ag. $\geq$ 60%).

B.2 Sensitivity to Suppression in QCEW Data

Table B.2. Estimation Results without the QCEW Data Imputed from MSA Totals

Panel A: Overall AI Innovation

	Employment Rate in All Agriculture		Employment Rate in Crop Production		Employment Rate in Animal Production	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Non-AI innovation	-0.613***	-0.427	-0.218***	-0.608***	-0.535***	-0.601**
	(0.221)	(0.342)	(0.082)	(0.166)	(0.172)	(0.237)
AI innovation	0.583***	0.406	0.182**	0.525***	0.492***	0.553***
	(0.198)	(0.308)	(0.072)	(0.147)	(0.155)	(0.213)
FE by Year	X	X	X	X	X	X
FE by CZ	X	X	X	X	X	X
Num.Obs.	4290	4290	4290	4290	4290	4290
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		492.969		501.221		489.173
KP Wald F-stat		187.883		188.594		185.927

Panel B: AI Innovations by Functional Domains

	Employment Rate in All Agriculture		Employment Rate in Crop Production		Employment Rate in Animal Production	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Non-AI innovation	-0.384*	-0.395	-0.134	-0.415***	-0.516***	-0.439**
	(0.224)	(0.279)	(0.085)	(0.124)	(0.167)	(0.184)
Execution-AI innovation	-1.112***	-0.987***	-0.463***	-0.740***	-0.582***	-0.284
	(0.237)	(0.313)	(0.116)	(0.162)	(0.162)	(0.196)
Cognition-AI innovation	0.411*	0.478	0.143*	0.493***	0.409***	0.244
	(0.213)	(0.292)	(0.085)	(0.141)	(0.153)	(0.187)
Perception-AI innovation	1.131***	0.907***	0.435***	0.576***	0.729***	0.562***
	(0.236)	(0.255)	(0.101)	(0.111)	(0.174)	(0.166)
FE by Year	X	X	X	X	X	X
FE by CZ	X	X	X	X	X	X
Num.Obs.	4290	4290	4290	4290	4290	4290
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		283.848		282.025		284.748
KP Wald F-stat		102.276		100.110		102.885

Notes: Robust standard errors clustered at the commuting-zone level are reported in parentheses. ***p ¡ 0.01, **p ¡ 0.05, *p ¡ 0.10. The dependent variable is the change in the number of employees in the respective subsector per 1,000 working-age individuals. The independent variables are changes in exposure to AI and non-AI innovations, constructed using shift–share measures. The first-stage Cragg–Donald Wald F-statistic and Kleibergen–Paap Wald F-statistic both exceed the Stock–Yogo critical values.

Table B.3. Estimation Results without the bottom ten QCEW-suppressed states

Panel A: Overall AI Innovation

	Employment Rate in All Agriculture		Employment Rate in Crop Production		Employment Rate in Animal Production	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Non-AI innovation	-0.480**	-0.167	-0.200**	-0.749***	-0.444**	-0.347
	(0.239)	(0.388)	(0.092)	(0.196)	(0.186)	(0.269)
AI innovation	0.474**	0.186	0.175**	0.660***	0.406**	0.320
	(0.214)	(0.345)	(0.081)	(0.174)	(0.165)	(0.238)
FE by Year	X	X	X	X	X	X
FE by CZ	X	X	X	X	X	X
Num.Obs.	3394	3394	3396	3396	3398	3398
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		334.981		343.164		333.264
KP Wald F-stat		130.833		131.725		128.359

Panel B: AI Innovations by Functional Domains

	Employment Rate in All Agriculture		Employment Rate in Crop Production		Employment Rate in Animal Production	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Non-AI innovation	-0.389	-0.438	-0.090	-0.487***	-0.510***	-0.454**
	(0.241)	(0.300)	(0.090)	(0.127)	(0.180)	(0.203)
Execution-AI innovation	-1.065***	-1.164***	-0.413***	-0.799***	-0.596***	-0.448**
	(0.253)	(0.338)	(0.119)	(0.168)	(0.172)	(0.212)
Cognition-AI innovation	0.508**	0.685**	0.089	0.561***	0.459***	0.359*
	(0.227)	(0.307)	(0.088)	(0.145)	(0.170)	(0.218)
Perception-AI innovation	0.950***	0.851***	0.416***	0.649***	0.647***	0.571***
	(0.249)	(0.283)	(0.106)	(0.118)	(0.189)	(0.185)
FE by Year	X	X	X	X	X	X
FE by CZ	X	X	X	X	X	X
Num.Obs.	3394	3394	3396	3396	3398	3398
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		183.491		181.096		184.647
KP Wald F-stat		51.467		50.185		51.721

Notes: Robust standard errors clustered at the commuting-zone level are reported in parentheses. ***p ¡ 0.01, **p ¡ 0.05, *p ¡ 0.10. The dependent variable is the change in the number of employees in the respective subsector per 1,000 working-age individuals. The independent variables are changes in exposure to AI and non-AI innovations, constructed using shift–share measures. The first-stage Cragg–Donald Wald F-statistic and Kleibergen–Paap Wald F-statistic both exceed the Stock–Yogo critical values.

B.3 Sensitivity to Partial Coverage of H-2A Employment in QCEW Data

Table B.4. Crop Sector Estimation Results with NAICS 115115 (i.e., Contracted H-2A) Employment

Panel A: Overall AI Innovation

	Employment Rate in Crop Production		Employment Rate in Crop Production		Employment Rate in Crop Production	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Non-AI innovation	-0.232***	-0.583***	-0.145*	-0.561***	-0.142*	-0.509***
	(0.080)	(0.166)	(0.083)	(0.164)	(0.085)	(0.167)
AI innovation	0.197***	0.506***	0.130*	0.496***	0.132*	0.454***
	(0.070)	(0.148)	(0.073)	(0.146)	(0.074)	(0.148)
FE by Year	X	X	X	X	X	X
FE by CZ	X	X	X	X	X	X
Add NAICS 115115	X	X			X	X
Only NAICS 115115			X	X	X	X
Num.Obs.	4626	4626	3883	3883	3883	3883
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		546.840		416.531		418.061
KP Wald F-stat		199.561		167.747		168.965

Panel B: AI Innovations by Functional Domains

	Employment Rate in Crop Production		Employment Rate in Crop Production		Employment Rate in Crop Production	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Non-AI innovation	-0.123	-0.421***	-0.096	-0.427***	-0.111	-0.449***
	(0.078)	(0.110)	(0.084)	(0.114)	(0.086)	(0.119)
Execution-AI innovation	-0.352***	-0.664***	-0.324***	-0.614***	-0.293***	-0.628***
	(0.107)	(0.151)	(0.105)	(0.146)	(0.110)	(0.154)
Cognition-AI innovation	0.091	0.452***	0.126	0.510***	0.145*	0.548***
	(0.077)	(0.126)	(0.083)	(0.132)	(0.082)	(0.136)
Perception-AI innovation	0.387***	0.574***	0.281***	0.455***	0.246**	0.448***
	(0.092)	(0.102)	(0.093)	(0.102)	(0.097)	(0.107)
FE by Year	X	X	X	X	X	X
FE by CZ	X	X	X	X	X	X
Add NAICS 115115	X	X			X	X
Only NAICS 115115			X	X	X	X
Num.Obs.	4626	4626	3883	3883	3883	3883
SE Cluster level:	CZ	CZ	CZ	CZ	CZ	CZ
CD Wald F-stat		281.739		237.891		237.282
KP Wald F-stat		61.589		48.523		48.522

Notes: Robust standard errors clustered at the commuting-zone level are reported in parentheses. ***p ¡ 0.01, **p ¡ 0.05, *p ¡ 0.10. The dependent variable is the change in the number of employees in the respective subsector per 1,000 working-age individuals. The independent variables are changes in exposure to AI and non-AI innovations, constructed using shift–share measures. The first-stage Cragg–Donald Wald F-statistic and Kleibergen–Paap Wald F-statistic both exceed the Stock–Yogo critical values. *Add NAICS 115115* adds employment from NAICS 115115 (Farm Labor Contractors and Crew Leaders) to total crop-sector employment. *Only NAICS 115115* restricts the sample to counties with employment in this category.

Supplemental Online Materials for "Artificial Intelligence (AI) and Agricultural Employment"

Table S1. Additional CPC Codes Mapped onto Agricultural Sectors

CPC Code	Title	111	112	113	114
Y02A40/10	Adaptation technologies in agriculture	Y			
Y02A40/13	Abiotic stress adaptation	Y			
Y02A40/132	Plants tolerant to drought	Y			
Y02A40/135	Plants tolerant to salinity	Y			
Y02A40/138	Plants tolerant to heat	Y			
Y02A40/146	New plants; transgenic processes	Y			
Y02A40/20	Fertilizers of biological origin	Y			
Y02A40/22	Improving land or water use; Controlling erosion	Y			
Y02A40/25	Greenhouse technology, e.g. cooling systems therefor	Y			
Y02A40/28	Specially adapted for farming	Y			
Y02A40/51	Specially adapted for storing farm products	Y			
Y02A40/58	Using renewable energies in agriculture	Y			
Y02W30/40	Production of fertilizers from waste or refuse	Y			
A01J1	Devices or accessories for milking by hand		Y		
A01J3	Milking with catheters		Y		
A01J5	Milking machines or devices		Y		
A01J7	Accessories for milking machines or devices		Y		
A01J9	Milk receptacles		Y		
A01J11	Apparatus for treating milk		Y		
A01L1	Shoes for horses or other solipeds fastened with nails		Y		
A01L3	Horseshoes fastened by means other than nails		Y		
A01L5	Horseshoes made of elastic materials		Y		
A01L7	Accessories for shoeing animals		Y		
A01L9	Shoes for other animals, e.g. oxen		Y		
A01L11	Farriers' tools and appliances		Y		
A01L13	Pens for animals while being shod		Y		
A01J15	Apparatus or use of substances for the care of hoofs		Y		
C05	Fertilizers; Manufacture thereof	Y			
A01B	Soil working in agriculture or forestry	Y		Y	
A01C	Planting; Sowing; Fertilizing	Y			
A01D	Harvesting; Mowing	Y			
A01F	Processing, Pressing, or Storing harvested produce	Y			
A01H	New plants; non-transgenic processes	Y			
A01N	Biocides, Pest repellent, plant growth regulators, or preservation (exc. A01N1–Preservation of animals)	Y			
A01L13	Pens for animals while being shod		Y		
A01J15	Apparatus or use of substances for the care of hoofs		Y		

Table S1. Additional CPC Codes Mapped onto Agricultural Sectors (continued)

CPC Code	**Title**	**111**	**112**	**113**	**114**
A01K1	Housing animals; Equipment therefor		Y		
A01K3	Pasturing equipment		Y		
A01K5	Feeding devices for stock or game		Y		
A01K7	Watering devices for stock or game		Y		
A01K9	Sucking apparatus for young stock		Y		
A01K11	Marking of animals		Y		
A01K13	Devices for grooming or caring of animals		Y		
A01K14	Removing the fleece from live sheep or similar animals		Y		
A01K15	Devices for taming animals, e.g. nose-rings or hobbles		Y		
A01K17	Dehorners; Horn trainers		Y		
A01K19	Weaning apparatus		Y		
A01K21	Devices for assisting or preventing mating		Y		
A01K23	Manure or urine pouches		Y		
A01K25	Muzzles		Y		
A01K27	Leads or collars, e.g. for dogs		Y		
A01K29	Other apparatus for animal husbandry		Y		
A01K31	Housing birds		Y		
A01K33	Nest-eggs		Y		
A01K35	Marking poultry or other birds		Y		
A01K37	Constraining birds, e.g. wing clamps		Y		
A01K39	Feeding or drinking appliances for poultry or similar		Y		
A01K41	Incubators for poultry		Y		
A01K43	Testing, sorting or cleaning eggs		Y		
A01K45	Other aviculture appliances, e.g. bird lay predictor		Y		
A01K47	Beehives		Y		
A01K49	Rearing-boxes; Queen transporting, introducing cages		Y		
A01K51	Appliances to clean or treat beehives or parts thereof		Y		
A01K53	Feeding or drinking appliances for bees		Y		
A01K55	Bee-smokers; Bee-keepers' accessories, e.g. veils		Y		
A01K57	Appliances to prevent swarms; Drone-catching devices				Y
A01K59	Honey collection		Y		
A01K61	Culture of aquatic animals		Y		
A01K63	Receptacles for live fish, e.g. aquaria		Y		
A01K65	Fish stringers		Y		
A01K67	Rearing or breeding animals, not otherwise provided for; New or modified breeds of animals		Y		
Y02A40/70	Adaptation technologies in livestock or poultry		Y		
Y02P60/50	Mitigation technologies in livestock or poultry		Y		
A01K2207	Modified animals		Y		
A01K2207	Genetically modified animals		Y		
A01K2207	Animals characterized by species		Y		
A01K2207	Animals characterized by purpose		Y		
A01G23	Forestry			Y	
A01B13	Ploughs or like machines for special purposes: Forestry			Y	
Y02P60/40	Afforestation or reforestation			Y	

Table S1. Additional CPC Codes Mapped onto Agricultural Sectors (continued)

CPC Code	**Title**	**111**	**112**	**113**	**114**
Y02A40/60	Ecological corridors or buffer zones			Y	
A01M	Catching, Trapping, or scaring of animals				Y
Y02A40/80	Adaptation technologies in fisheries management				Y
Y02P60/60	Mitigation technologies in Fishing or Aquaculture		Y		Y
A01K69	Stationary catching devices				Y
A01K71	Floating nets				Y
A01K73	Drawn nets				Y
A01K74	Other catching nets or the like				Y
A01K75	Accessories for fishing nets; Details of fishing net				Y
A01K77	Landing-nets for fishing; Landing-spoons for fishing				Y
A01K79	Methods or means of catching fish in bulk				Y
A01K80	Harvesting oysters, mussels, sponges or the like				Y
A01K81	Fishing with projectiles				Y
A01K83	Fish-hooks				Y
A01K85	Artificial bait for fishing				Y
A01K87	Fishing rods				Y
A01K89	Reels				Y
A01K91	Lines				Y
A01K93	Floats for angling, with or without signaling devices				Y
A01K95	Sinkers for angling				Y
A01K97	Accessories for angling				Y
A01K99	Other methods or apparatus for fishing				Y

Notes: In addition to the original mapping of patent CPC codes to agricultural subsectors, this table lists newer CPC codes relevant to agriculture that post-date Goldschlag et al. (2020). Columns 111–114 indicate NAICS subsectors: 111 (Crop Production), 112 (Animal Production and Aquaculture), 113 (Forestry and Logging), and 114 (Fishing, Hunting and Trapping).