Digital Agricultural Information and Agricultural Technology Histories in Nigeria

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Abstract

Agricultural information can change technology decisions, but households observed using digital agricultural information do not enter that comparison with identical agricultural histories. Using the 2018/19 and 2023/24 waves of the Nigeria General Household Survey Panel, this paper looks backwards from contemporary digital agricultural-information engagement to the same households' technology use approximately five years earlier. The historical differences are large for some technologies and nearly absent for others. Households subsequently observed as digitally engaged were already 15.5 percentage points more likely to use herbicide, 10.4 points more likely to use inorganic fertiliser and 8.6 points more likely to use tractors; earlier pesticide use differed by only 0.3 points and organic-fertiliser use was 2.8 points lower. For herbicide, the contemporary digital differential is 11.37 percentage points in the unrestricted 2023/24 sample and 2.06 points after earlier herbicide use and state are incorporated. Tractor shows a similar reduction, while pesticide, inorganic fertiliser and organic fertiliser follow different paths. The estimates are not causal. Their contribution is to show that observed digital-information engagement is situated within technology-specific agricultural histories and spatial environments. Contemporary digital/non-digital comparisons can therefore reflect differences that were already visible in the agricultural system years earlier.

1. Introduction

Digital agricultural information is usually studied for what it may change: farmers' knowledge, input choices, productivity or market decisions. Observational data pose a prior problem. By the time digital agricultural-information engagement is observed, the households being compared may already occupy different positions in the agricultural system. Those positions can shape information demand, access and contact with service providers, while also being related to the technologies farmers use. A contemporary digital/non-digital comparison can therefore contain agricultural differences that did not begin with the contemporary information measure. This distinction matters because observed digital engagement emerges from information demand, access and service delivery within an agricultural system, rather than being assigned independently of farmers' existing production choices.

The difficulty is that most contemporary household data cannot look backwards. Rich current-period controls can describe farms when digital engagement is observed, but they cannot show whether the same households were already using agricultural technologies differently years earlier. The Nigeria GHS-Panel can. Wave 5 records digital agricultural-information engagement, while the panel identifies the same households' technology use in 2018/19. This makes it possible to ask whether the contemporary comparison is preceded by observable differences in agricultural technology positions, whether those differences are common across technologies, and how the contemporary association changes when earlier behaviour and geography are brought into view.

A broader literature establishes why information belongs in models of agricultural technology diffusion. Conley and Udry (2010) show that farmers adjust input choices in response to the experience of successful information neighbours. Van Campenhout (2021) experimentally studies technical and returns

information for rice intensification in Uganda and finds that information effects depend importantly on peer spillovers. Aker, Ksoll and Lybbert (2016) show that improved access to and capacity to use mobile phones can change crop choices without automatically improving marketing outcomes. These studies establish that information and its transmission can affect agricultural decisions. They do not imply that naturally observed information engagement is independent of farmers' existing technology positions.

The Nigerian literature makes this distinction especially useful. Oyinbo et al. (2022) identify responses to deliberately supplied digital nutrient-management information in a randomised experiment. Kouandou and Laajimi (2026) study smartphone ownership and agricultural intensification in nationally representative data, including relationships with phytosanitary inputs and tractor use. Daudu and Orkoh (2026) use GHS-Panel data to examine digital extension, agricultural income and food security. The question here is different. Rather than treating a contemporary digital comparison as the starting point, the panel is used to look backwards at the same households and ask how much agricultural differentiation was already observable before the Wave-5 information measure was recorded.

The analysis uses Waves 4 and 5 of the Nigeria General Household Survey Panel. Wave 5 contains a dedicated Digital Farming Information module recording agricultural information obtained or searched for through a mobile phone, through an agent using a digital device, or through both. The panel links these observations to agricultural behaviour in 2018/19. Five outcomes are retained throughout: herbicide, pesticide, inorganic fertiliser, organic fertiliser and tractor use.

The backward comparison reveals a pattern that is neither small nor uniform. Households subsequently observed as digitally engaged were already 15.5 percentage points more likely to use herbicide, 10.4 points more likely to use inorganic fertiliser and 8.6 points more likely to use tractors. Yet earlier pesticide use differs by only 0.3 points, and organic-fertiliser use is 2.8 points lower. This is not a general gradient in which households subsequently observed as digitally engaged used more of every technology. It is technology-specific. The contemporary estimates are equally heterogeneous: the herbicide association moves from 11.37 percentage points in the unrestricted sample to 2.06 after earlier herbicide use and state adjustment, while tractor moves from 6.85 to 0.93. Pesticide, inorganic fertiliser and organic fertiliser do not follow the same path.

The contribution is to make the history behind a contemporary digital comparison observable. For herbicide, that history is not confined to persistence in herbicide use: with state fixed effects, controlling for the other four Wave-4 technologies moves the coefficient from 2.79 to 2.04 percentage points, close to the 2.06 estimate obtained when earlier herbicide itself is included. Tractor is different; persistence in tractor use accounts for more of the adjustment. The panel therefore shows where earlier agricultural positioning matters, where it does not, and whether the relevant history is specific to the same technology or extends across a wider technology portfolio.

The estimates are not causal. Wave 4 precedes measurement of Wave-5 digital-information engagement, but the survey does not reveal when a household first began using digital agricultural information. Earlier technology use may be related to subsequent information demand, access or provider contact, and both earlier technology use and later engagement may share unobserved determinants. The analysis does not distinguish these mechanisms. It establishes the narrower empirical fact that contemporary digital-information engagement is systematically composed across households whose technology positions and spatial environments were already heterogeneous years earlier.

2. Digital information, technology use and prior observed differences

Agricultural information can alter technology decisions by changing knowledge of implementation, expected returns or the experience of peers. Conley and Udry (2010) document social learning in input decisions among pineapple farmers in Ghana. Van Campenhout (2021) shows experimentally that technical and returns information can affect rice intensification in Uganda once information spillovers

between farmers are recognised. Aker, Ksoll and Lybbert (2016) show that improved mobile-phone access and skills changed crop diversification in Niger, while effects on crop sales and farm-gate prices were limited. Information can therefore matter without producing a uniform response across technologies or outcomes.

Digital delivery adds a further distinction between assigned information and observed engagement. Oyinbo et al. (2022) show that site-specific nutrient-management recommendations delivered through a digital decision-support tool can improve fertiliser management and maize yields under a randomised design in northern Nigeria. Their design identifies responses to deliberately supplied information. The present paper instead studies naturally observed agricultural-information engagement, for which farmers' existing technology positions may be related to whether and how they enter the observed information environment.

Kouandou and Laajimi (2026) examine smartphone ownership and agricultural intensification in Nigeria and report positive relationships with several production choices, including phytosanitary inputs and tractor use. Smartphone ownership is an economically relevant measure of digital access, but ownership and agricultural-information engagement are not equivalent exposures.

Daudu and Orkoh (2026) use GHS-Panel data to study digital extension services, agricultural income and food security through a gender lens. Their outcomes and empirical question differ from those studied here. This paper links observed agricultural-information engagement to technology-specific histories for the same households and traces how contemporary associations change with longitudinal observability, earlier technology use and geography.

Systematic composition in observed engagement matters economically because information demand, access and service delivery can each be related to the farm's existing production system. Farmers already using purchased inputs or machinery may value additional information differently, have different advisory needs, face different access conditions or have greater contact with service providers. Location can also jointly shape information access and technology use through crop systems, markets, extension infrastructure and connectivity. The data cannot distinguish these mechanisms, so earlier technology histories and state fixed effects are used as diagnostics of composition rather than as a causal model of digital engagement.

Earlier same-household behaviour is used to document prior observed differences, not as a substitute for causal identification. The analysis asks whether households subsequently observed engaging with digital agricultural information were already different in technology use, whether those differences are technology-specific or reflect a wider technology portfolio, and how the contemporary association changes when comparison is restricted within states.

3. Data and measurement

3.1 Nigeria General Household Survey Panel

The analysis uses Waves 4 and 5 of the Nigeria General Household Survey Panel, implemented by Nigeria’s National Bureau of Statistics with support from the World Bank Living Standards Measurement Study. Wave 4 was conducted in 2018/19 and Wave 5 in 2023/24. Wave 5 contains a dedicated Digital Farming Information module with 4,771 household records in the analytical file. Of these, 4,682 have a positive Wave 4–Wave 5 longitudinal weight. The principal longitudinal analyses use wt_wave5 and account for the original stratified primary-sampling-unit design.

3.2 Digital agricultural-information engagement

The main explanatory variable identifies households reporting agricultural information or advice obtained through a mobile phone, through an agent using a digital device, or through both routes. It

captures realised engagement with digitally mediated agricultural information rather than device ownership. A stricter robustness definition requires an explicitly observed mobile or internet information channel: telephone calls, SMS, WhatsApp, Facebook, websites, mobile applications or self-directed internet searches. These channel items belong to the agricultural-information pathway of the questionnaire. A separate set of similarly worded variables concerns digital input or equipment purchasing and is excluded from both exposure definitions.

Table 2. Measurement of digital agricultural-information engagement in 2023/24

Definition	Observed route/channel	Raw item	Interpretation
Main	Mobile phone	s12q2 = 1	Agricultural information/advice obtained via a mobile phone
Main	Agent with digital device	s12q2 = 2	Agricultural information/advice obtained from an agent using a digital device
Main	Both routes	s12q2 = 3	Both mobile phone and digitally equipped agent
Strict	Phone call	s12q4__1 = 1	Explicit mobile channel
Strict	SMS	s12q4__3 = 1	Explicit mobile channel
Strict	WhatsApp	s12q4__5 = 1	Explicit mobile/internet channel
Strict	Facebook	s12q4__6 = 1	Explicit mobile/internet channel
Strict	Website	s12q4__7 = 1	Explicit internet channel
Strict	Mobile application	s12q4__8 = 1	Explicit mobile/internet channel
Strict	Self-directed internet search	s12q4__9 = 1	Google, YouTube or other self-directed internet search

Notes: The main exposure equals one for s12q2 categories 1-3. The strict exposure equals one when any listed s12q4 channel is observed. Variables s12q33__* concern a separate digital input/equipment purchasing pathway and are excluded.

3.3 Agricultural technology outcomes

Five binary outcomes are examined: herbicide, pesticide, inorganic fertiliser, organic fertiliser and tractor use. Plot-level records are collapsed to household indicators. A household is coded as a user when at least one observed eligible plot reports use; missing observations are not automatically classified as zero. The corresponding Wave-4 outcome is harmonised separately for each technology.

3.4 Paired histories and sample construction

For herbicide, pesticide, inorganic fertiliser and organic fertiliser, 2,207 households have the corresponding outcome observed in both waves, including 322 digitally informed households. Tractor use has a paired sample of 2,954 households, including 435 digitally informed households. Because paired-history availability differs by subsequent digital status, the sequential analysis makes the change produced by imposing this sample visible before historical controls are introduced.

4. Empirical strategy

For each technology, the analysis follows a sequential coefficient-sensitivity design. Let i index households, k technologies and t survey waves. Y_ik5 denotes household i's Wave-5 use of technology k, D_i5 indicates Wave-5 digital agricultural-information engagement, and Y_ik4 denotes the corresponding Wave-4 technology indicator. The unrestricted contemporary association is:

$$Y_{ik5} = \alpha_k + \beta_k UD_{i5} + \varepsilon_{ik5}$$

The same equation is re-estimated on the technology-specific paired-history sample, yielding β^P_k. Holding that sample fixed, the household's own earlier use of the same technology is then introduced:

$$Y_{ik5} = \alpha_k + \beta_k HD_{i5} + \gamma_k Y_{ik4} + \varepsilon_{ik5}$$

The finer geographic-adjustment endpoint adds state fixed effects, δ_s:

$$Y_{ik5} = \alpha_k + \beta_k SD_{i5} + \gamma_k Y_{ik4} + \delta_s + \varepsilon_{ik5}$$

Comparing the four specifications shows how the estimated contemporary association changes as the analysis moves from the unrestricted Wave-5 sample to the paired sample, and then incorporates earlier technology use and state fixed effects. The changes are interpreted as sensitivity to the information introduced at each stage, rather than as causal contributions attributable to sample selection, prior behaviour or geography. Weighted linear probability models are used because the quantities of interest are probability differences in technology use. A separate robustness exercise holds the state-adjusted sample fixed and compares four specifications: state fixed effects alone; the other four Wave-4 technologies, deliberately excluding the outcome's own history; the outcome's own Wave-4 history; and all five Wave-4 technologies. This distinguishes broader technology-history information from persistence in the same outcome.

A separate weighted logit model describes observable selection into subsequent digital engagement. X_i contains exactly five Wave-4 technology indicators (herbicide, pesticide, inorganic fertiliser, organic fertiliser and tractor use), sector and state. The complete-case sample contains 3,292 households, including 459 households subsequently observed as digitally engaged. The estimated propensity score is:

$$e_i = Pr(D_{i5} = 1 \mid X_i) = \frac{exp(X_i'\theta}{1 + exp(X_i'\theta}.$$

Let w_i denote the official longitudinal survey weight. Overlap weighting combines that survey weight with the estimated propensity score as:

$$\omega_i = w_i[\, D_{i5}(1 - e_i) + (1 - D_{i5})e_i \,].$$

Digitally engaged households receive the factor 1 - e_i and other households receive e_i, with both multiplied by the official longitudinal survey weight. The weighting exercise concentrates the comparison on households with greater overlap in the included histories and geography. It does not address unmeasured selection or identify a causal effect.

5. Results

5.1 Earlier observed differences

Technology	Not digitally engaged in W5 (%)	Digitally engaged in W5 (%)	Difference (pp)	SMD
Herbicide	38.6	54.1	15.5	0.315
Pesticide	19.4	19.7	0.3	0.008

Technology	Not digitally engaged in W5 (%)	Digitally engaged in W5 (%)	Difference (pp)	SMD
Inorganic fertiliser	41.8	52.1	10.4	0.209
Organic fertiliser	28.6	25.8	-2.8	-0.063
Tractor	9.9	18.5	8.6	0.249

Note: Percentages are Wave-4 technology-use rates, weighted with the Wave-4 survey weight, among households classified by their subsequently observed Wave-5 digital agricultural-information engagement status. The descriptive comparison uses complete Wave-4 technology observations available for the propensity-score diagnostic sample (N = 3,292; 459 subsequently digitally engaged households). SMD denotes the standardised mean difference.

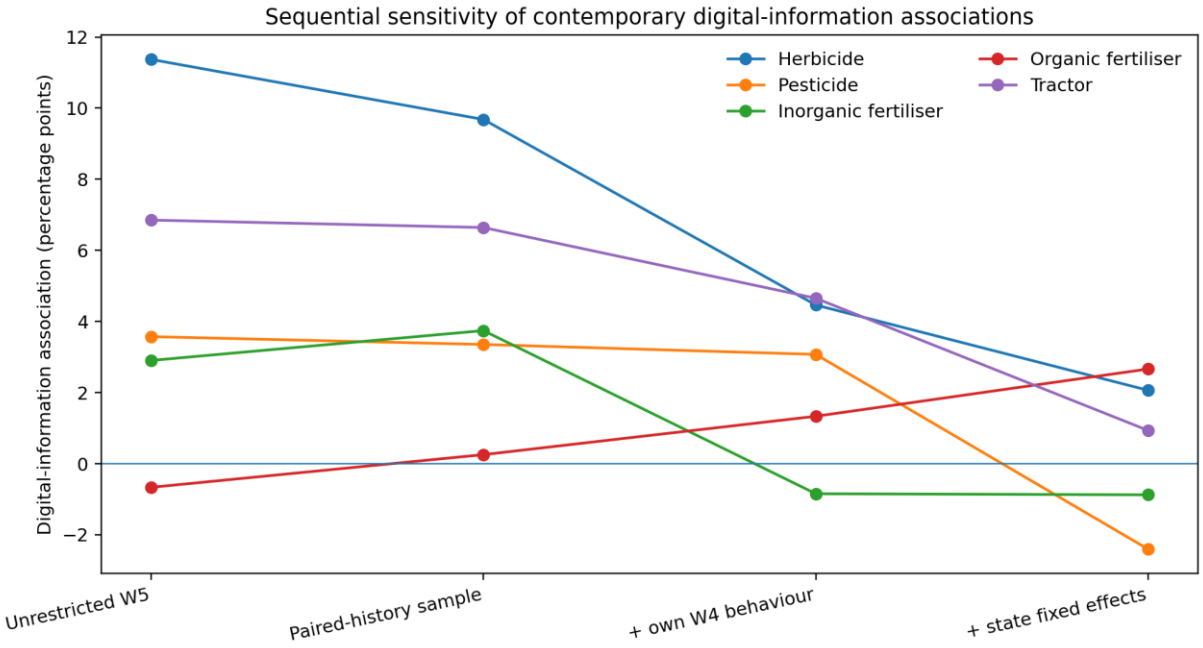
The first result is visible before any contemporary regression is estimated. Households later observed as digitally engaged were already more likely to use herbicide, inorganic fertiliser and tractors in 2018/19. Weighted herbicide use was 54.1 per cent among households subsequently observed as digitally engaged and 38.6 per cent among those not digitally engaged in Wave 5; tractor use was 18.5 and 9.9 per cent, respectively. Yet pesticide use was almost identical across the two groups and organic-fertiliser use was slightly lower among households subsequently observed as digitally engaged. The historical difference is therefore concentrated in particular technologies rather than reflecting uniformly higher technology use among households that later appear in the digital-information group.

5.2 Sequential coefficient sensitivity

Outcome	Unrestricted W5	Paired sample	+ earlier own use	+ state FE	Final SE	Paired N
Herbicide	11.37	9.68	4.46	2.06	3.84	2207
Pesticide	3.57	3.35	3.07	-2.41	3.4	2207
Inorganic fertiliser	2.9	3.74	-0.85	-0.88	3.67	2207
Organic fertiliser	-0.67	0.25	1.33	2.66	2.84	2207
Tractor	6.85	6.64	4.65	0.93	2.44	2954

Looking backwards changes the interpretation of the two largest contemporary differentials. Herbicide is 11.37 percentage points higher among digitally engaged households in the unrestricted Wave-5 comparison and 9.68 points higher when the sample is restricted to households with paired histories. On that same paired sample, the estimate falls to 4.46 points after earlier herbicide use is introduced and to 2.06 points with state adjustment. Tractor moves from 6.85 to 6.64, 4.65 and 0.93 points across the same sequence. The small unrestricted-to-paired changes show that sample restriction is not doing most of the work for these outcomes. The larger changes appear when information about earlier behaviour and spatial environment becomes available.

Figure 1. Sequential coefficient sensitivity across specifications



The remaining technologies prevent a simple 'digital farmers were already more modern' interpretation. Inorganic fertiliser changes sign after earlier use is introduced, pesticide becomes negative after state adjustment, and organic fertiliser moves away from zero. Historical and geographic adjustment therefore does not mechanically shrink every coefficient. Instead, the five outcomes reveal different relationships between contemporary digital-information engagement, earlier technology positions and place. That non-uniformity is part of the substantive result, not an inconvenience around the herbicide and tractor findings.

5.3 Overlap weighting

Overlap weighting provides a complementary comparison among households with greater overlap in the observed Wave-4 technology histories, sector and state. Before weighting, households subsequently observed as digitally engaged display meaningful imbalance in earlier herbicide, inorganic fertiliser and tractor use. As expected from the weighting construction, standardised mean differences for the five included technology histories are approximately zero after weighting. The effective sample size falls from about 1,622 to 718. The overlap-weighted contemporary differences are 0.16 percentage points for herbicide, -3.19 for pesticide, -0.53 for inorganic fertiliser, 4.28 for organic fertiliser and 0.66 for tractor use.

5.4 Alternative digital-information definition

A stricter exposure based on explicitly observed mobile or internet channels produces a similar pattern for the two largest unadjusted differentials. Herbicide moves from a paired-sample contemporary association of 9.51 percentage points to 1.92 percentage points after historical and state adjustment. Tractor moves from 6.45 to 0.82 percentage points. The headline sensitivity is therefore not driven by including digitally equipped intermediaries in the broader exposure.

6. Robustness and identification limits

Each robustness check addresses a different source of uncertainty. The strict exposure changes the definition of digital engagement. Overlap weighting changes the comparison by reweighting observed histories and geography. The sequential specifications distinguish paired-history observability from subsequent historical and geographic adjustment. The leave-own-out specification tests whether a wider earlier technology portfolio matters independently of persistence in the same outcome. The all-five specification combines both sources of historical information. Leave-one-state-out estimates assess dependence on individual states, while attrition is examined separately from outcome-specific paired-history availability.

Panel attrition warrants inspection but is modest in absolute terms. Raw Wave-5 completion among the eligible Wave-4 sample is approximately 95.1 per cent and the Wave-4-weighted completion rate approximately 94.3 per cent. Retention varies somewhat with earlier technology use. The official Wave-5 documentation states that the combined-sample longitudinal weights use Wave-4 weights as the base, adjust for Wave-4-to-Wave-5 attrition/non-response through a modelled response propensity, and are calibrated to the target population. The main analysis therefore uses wt_wave5 directly and does not multiply it by a second, researcher-estimated attrition weight.

Outcome-specific paired-history availability is analytically distinct from panel attrition. Among the 4,682 households with positive longitudinal weights, 2,207 enter the paired input-outcome samples and 2,954 enter the paired tractor sample. The unrestricted-to-paired step makes the resulting selection visible before historical controls are introduced.

State fixed effects provide a demanding geographic-adjustment endpoint. Thirty-five of the 37 represented state/FCT categories contain both digital and non-digital households and account for more than 98 per cent of paired observations, although digital observations are thin in some states. A leave-one-state-out exercise gives herbicide coefficients from -0.34 to 3.62 percentage points and tractor coefficients from -0.11 to 2.81 across the 37 omissions. No single omission restores the paired-sample differentials of 9.68 and 6.64 percentage points. The large movement between earlier-behaviour and state-adjusted specifications is therefore interpreted as sensitivity to spatial composition. State may capture differences in crop systems, markets, extension, connectivity and other agricultural environments; the design does not identify which of these mechanisms is responsible.

The leave-own-out specification separates broader technology history from persistence in the same outcome. With state fixed effects and the same analytic samples, the herbicide coefficient is 2.79 percentage points before technology-history controls, 2.04 after controlling for the other four Wave-4 technologies, 2.06 after controlling for earlier herbicide use, and 1.70 when all five earlier technologies enter together. For tractor, the corresponding estimates are 1.89, 1.52, 0.93 and 0.66 percentage points. Broader technology history therefore contains information beyond the own lag for herbicide, while own-technology persistence is more important for tractor. For pesticide, inorganic fertiliser and organic fertiliser, the leave-own-out estimates are -2.46, 0.19 and 2.00 percentage points, respectively. None of these specifications requires additional complete-case exclusions.

The analysis does not estimate a causal effect of digital agricultural information. Wave 4 predates the Wave-5 digital-information measure but is not a verified baseline before first digital exposure. Unobserved persistent characteristics, time-varying confounding and measurement error remain possible. Overlap weighting balances observed characteristics only.

Table 5. Robustness of state-adjusted digital-information associations

Outcome	State only	Other 4 W4 + state	Own W4 + state	All 5 W4 + state	Strict exposure + state	Leave-one-state-out range
Herbicide	2.79 (4.01)	2.04 (3.78)	2.06 (3.84)	1.70 (3.67)	1.92	-0.34 to 3.62

Outcome	State only	Other 4 W4 + state	Own W4 + state	All 5 W4 + state	Strict exposure + state	Leave-one-state-out range
Pesticide	-2.16 (3.39)	-2.46 (3.43)	-2.41 (3.40)	-2.53 (3.45)	-3.06	—
Inorganic fertiliser	0.25 (3.66)	0.19 (3.51)	-0.88 (3.67)	-0.87 (3.57)	0.40	—
Organic fertiliser	2.64 (2.85)	2.00 (2.81)	2.66 (2.84)	2.02 (2.82)	2.64	—
Tractor	1.89 (2.41)	1.52 (2.37)	0.93 (2.44)	0.66 (2.42)	0.82	-0.11 to 2.81

Notes: Coefficients and design-based standard errors in parentheses are percentage points. 'Other 4 W4' excludes the outcome's own Wave-4 indicator. All four historical specifications use the same outcome-specific analytic sample. Strict-exposure entries report the corresponding state-adjusted coefficient. Leave-one-state-out ranges are shown for herbicide and tractor.

7. Conclusion

The main empirical advantage of the panel is simple: it permits the contemporary digital comparison to be viewed from five years earlier. From that earlier vantage point, households later observed in different digital agricultural-information environments were already differently positioned on several dimensions of technology use. The differences are large for herbicide, inorganic fertiliser and tractor use, negligible for pesticide use and reversed for organic fertiliser. Digital-information engagement is therefore associated with particular agricultural histories rather than with uniformly greater use of every technology.

Those histories materially change how the contemporary comparison reads. The herbicide and tractor differentials change little when the analysis is restricted to households observed in both waves, but become much smaller once earlier behaviour and geography are incorporated. For herbicide, the wider Wave-4 technology portfolio contains information even when earlier herbicide itself is omitted; for tractor, persistence in tractor use is more important. Neither a single state nor the broader exposure definition accounts for the headline pattern.

The contrasting outcomes are equally informative. Pesticide changes sign after geographic adjustment, inorganic fertiliser changes sign after earlier use is introduced, and organic fertiliser moves away from zero. These results make it difficult to reduce the findings to a single latent ranking of 'more modern' and 'less modern' farms. The composition of observed digital engagement is technology-specific and spatially organised.

The analysis does not estimate the effect of digital agricultural information, and Wave 4 is not a verified pre-treatment baseline. Its contribution is narrower and directly observable: some contemporary digital-agriculture differences sit on top of agricultural differences that were already present years earlier, while others do not. Panel histories reveal that distinction. Without them, a contemporary digital/non-digital coefficient can be easy to read as a difference associated with the information environment alone when part of the contrast may belong to the agricultural history of the households being compared.

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Appendix A. Sample construction and diagnostics

A1. Sample flow

Stage	N	Definition
Wave 5 completed interviews / digital-information module	4771	All completed W5 households represented in sect12
Positive Wave 5 longitudinal weight	4682	Eligible for W4-W5 longitudinal weighting
Herbicide/pesticide/fertiliser common analytic sample	2207	Non-missing paired W4-W5 outcome, exposure and design variables
Digital households in common analytic sample	322	Broad digital-information exposure
Tractor analytic sample	2954	Non-missing paired W4-W5 tractor, exposure and design variables
Digital households in tractor sample	435	Broad digital-information exposure

A2. Paired-history availability

Outcome	Digital	Eligible_N	Paired_N	Paired_rate_raw	Paired_rate_weighted
Herbicide	0	4103	1885	0.4594	0.4504
Herbicide	1	579	322	0.5561	0.5904
Pesticide	0	4103	1885	0.4594	0.4504
Pesticide	1	579	322	0.5561	0.5904
Inorganic fertiliser	0	4103	1885	0.4594	0.4504
Inorganic fertiliser	1	579	322	0.5561	0.5904
Organic fertiliser	0	4103	1885	0.4594	0.4504

Outcome	Digital	Eligible_N	Paired_N	Paired_rate_raw	Paired_rate_weighted
Organic fertiliser	1	579	322	0.5561	0.5904
Tractor	0	4103	2519	0.6139	0.6011
Tractor	1	579	435	0.7513	0.7617

A3. Paired-history exclusions

Outcome	Observation status	N	Digital_N	Digital_share	Weight_sum
Herbicide	Neither wave observed	1058	60	0.0567	6078331.5
Herbicide	W5 only	332	60	0.1807	2014673.6
Herbicide	W4 only	1085	137	0.1263	6242661.5
Herbicide	Paired	2207	322	0.1459	12621384.0
Pesticide	Neither wave observed	1058	60	0.0567	6078331.5
Pesticide	W5 only	332	60	0.1807	2014673.6
Pesticide	W4 only	1085	137	0.1263	6242661.5
Pesticide	Paired	2207	322	0.1459	12621384.0
Inorganic fertiliser	Neither wave observed	1058	60	0.0567	6078331.5
Inorganic fertiliser	W5 only	332	60	0.1807	2014673.6
Inorganic fertiliser	W4 only	1085	137	0.1263	6242661.5
Inorganic fertiliser	Paired	2207	322	0.1459	12621384.0
Organic fertiliser	Neither wave observed	1058	60	0.0567	6078331.5
Organic fertiliser	W5 only	332	60	0.1807	2014673.6
Organic fertiliser	W4 only	1085	137	0.1263	6242661.5
Organic fertiliser	Paired	2207	322	0.1459	12621384.0
Tractor	Neither wave observed	1030	55	0.0534	5919869.0
Tractor	W5 only	360	65	0.1806	2173136.5
Tractor	W4 only	338	24	0.071	2107713.0
Tractor	Paired	2954	435	0.1473	16756333.0

Appendix B. Variable construction

Herbicide: Wave 4 s11c2q10; Wave 5 s11c2q1. Pesticide: Wave 4 s11c2q1; Wave 5 s11c2q3. Inorganic fertiliser: Wave 4 s11dq1a; Wave 5 s11c2q5. Organic fertiliser: Wave 4 s11dq36; Wave 5 s11c2q11. Tractor: Wave 4 s11b1q11a; Wave 5 s11b1q69.