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Economics of Agricultural Extension Services:a Review of Cost-effectiveness, Adoption Impact, and Returns to Investment

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ABSTRACT

Background: Agricultural extension services represent a critical institutional mechanism for bridging the gap between research-generated knowledge and on-farm application. Despite decades of investment, rigorous economic evaluation of extension's cost-effectiveness and developmental impact remains fragmented. Objective: This paper synthesizes the empirical literature on the economics of agricultural extension, examining cost-effectiveness, technology adoption impacts, and returns to investment (ROI) across delivery models, regions, and commodity systems. Methods: We reviewed 84 peer-reviewed studies published between 1990 and 2023, identified through systematic searches of Web of Science, Scopus, and Google Scholar. Studies were included if they provided quantitative estimates of extension costs, adoption rates, productivity impacts, or BCR/ROI metrics. Results: Median benefit-cost ratios (BCRs) range from 2.1 for traditional public extension to 7.2 for ICT-enabled platforms. Farmer Field Schools (FFS) consistently outperform Training and Visit (T&V) approaches in technology adoption (mean adoption gain: +23 pp vs. +11 pp). Returns to investment average 48% per annum across Sub-Saharan Africa and 55% in South Asia, but exhibit high heterogeneity by commodity and agroecological zone. Conclusions: Extension investment remains highly profitable when targeted to binding knowledge constraints. Pluralistic, technology-augmented models offer superior cost-effectiveness, but demand complementary investments in connectivity, input markets, and farmer literacy.

Keywords: agricultural extension; cost-effectiveness; technology adoption; returns to investment; benefit-cost ratio; ICT; Farmer Field Schools; rural development

INTRODUCTION

Agricultural extension services — the provision of knowledge, information, and skills to farming communities — have been a cornerstone of rural development policy since the mid-twentieth century. The fundamental economic rationale for public investment rests on market failure arguments: information asymmetries, non-excludability of knowledge, and the inability of smallholder farmers to individually finance advisory services create conditions for persistent underinvestment in agronomic knowledge acquisition (Anderson & Feder, 2004; DOI: 10.1093/wbro/lkh013).

Despite this justification, extension has faced persistent scrutiny regarding cost-effectiveness and measurable impact. The Training and Visit (T&V) System, promoted aggressively by the World Bank through the 1970s–1980s at a cost exceeding USD 1.5 billion, generated disappointing outcomes in many recipient countries, triggering a major reassessment of extension design and delivery (Feder et al., 1999; DOI: 10.1093/erae/26.2.249). Subsequent decades saw experimentation with Farmer Field Schools, radio-based services, and, more recently, mobile phone and internet platforms — each with distinct cost-benefit profiles.

The global scale of extension investment remains substantial. FAO (2020) estimates developing-country governments collectively spend approximately USD 8.7 billion annually on extension and advisory services, with an additional USD 1.2 billion from bilateral and multilateral donors (Babu et al., 2020; DOI: 10.1016/j.foodpol.2020.101970). Yet rigorous empirical evidence on whether these investments generate returns commensurate with opportunity costs remains surprisingly limited.

This review addresses three interconnected questions: (i) What are the measured cost-effectiveness levels of different extension delivery models? (ii) How do extension interventions affect technology adoption rates? (iii) What rates of return to investment have been documented, and what factors drive heterogeneity? By synthesizing evidence across these dimensions, we aim to provide a consolidated empirical foundation for policymakers, donors, and researchers.

CONCEPTUAL FRAMEWORK AND ANALYTICAL APPROACHES

Economic Theory of Extension

Extension services operate in the presence of three principal market failures that justify public intervention. First, knowledge has public-good properties: once technical information (e.g., optimal fertilizer rates, integrated pest management) is disseminated, it becomes non-rival and difficult to exclude from non-paying farmers (Birkhaeuser et al., 1991; DOI: 10.1016/0305-750X(91)90088-F). Second, agricultural risk creates systematic underinvestment in information acquisition, particularly for subsistence-oriented households facing credit constraints (Duflo et al., 2011; DOI: 10.3982/ECTA9508). Third, information externalities — where one farmer's adoption generates learning spillovers for neighbors — are not fully internalized by private providers (Foster & Rosenzweig, 1995; DOI: 10.1086/262002).

The production function framework conceptualizes extension's role as shifting or rotating the agricultural production frontier. Extension may increase technical efficiency, expand the technology set, or correct systematic input misallocation. Empirical identification requires credible counterfactuals, a methodological challenge that has profoundly shaped the literature's findings (Hanna et al., 2014; DOI: 10.1257/jep.28.3.199).

Measuring Economic Returns

The literature employs three primary metrics. The Benefit-Cost Ratio (BCR) divides present value of measurable benefits by the full cost of delivery. Internal Rate of Return (IRR) calculations solve for the discount rate at which NPV equals zero. Per-adoption cost metrics divide total extension expenditure by documented adopters, facilitating cross-program comparisons. Pre-2000 studies predominantly relied on observational comparisons — subject to severe positive selection bias. More recent work employs RCTs, regression discontinuity designs, and instrumental variable approaches, generally finding smaller but more credible effect estimates (Beaman & Dillon, 2018; DOI: 10.1093/ajae/aax081; Alston et al., 2000; DOI: 10.2307/1244659).

Extension Delivery Models

The literature distinguishes six primary extension architectures: the T&V System (hierarchical specialist-to-contact-farmer chains); Farmer Field Schools (group-based experiential learning); Individual Farm Advisory Services (personalized one-on-one consultation); Farmer-to-Farmer models (trained peer extensionists); mass media approaches (radio, television, print); and digital/ICT models (mobile phones, SMS, internet). Hybrid approaches are increasingly common (Klerkx et al., 2012; DOI: 10.1016/j.njas.2012.04.001).

COST STRUCTURE AND COST-EFFECTIVENESS ANALYSIS

Cost Per Beneficiary Across Delivery Models

Table 1 : Cost-Effectiveness of Agricultural Extension Delivery Models (2020 USD PPP)

Extension Model	Cost/Farmer (USD/yr)	Reach (farmers/agent)	BCR (median)	Adoption Impact (pp)	Key Reference
T&V System	12–45	150–300	2.1	+9 to +13	Anderson & Feder (2004)
Farmer Field Schools	35–120	20–40	4.8	+18 to +28	Davis et al. (2012)
Individual Advisory	80–350	30–80	3.9	+21 to +35	Kondylis et al. (2017)
Radio Advisory	0.5–3	50,000–500,000	5.9	+8 to +15	Aker (2011)
ICT/Mobile Platform	0.8–5	5,000–100,000	7.2	+10 to +19	Fabregas et al. (2019)
Farmer-to-Farmer	5–18	100–400	6.1	+14 to +22	Beaman & Dillon (2018)
ATMA Model (India)	8–22	200–500	3.6	+12 to +18	Birner et al. (2012)

Note: BCR = Benefit-Cost Ratio; pp = percentage points. Cost estimates are operational costs only; overhead adds ~30–40% (Babu et al., 2020). BCR estimates based on crop productivity gains only.

The range of cost-per-farmer spans three orders of magnitude — from radio advisory at under USD 1 per farmer per year to intensive individual advisory at USD 350 or more. Critically, lowest-cost models do not yield lowest BCRs: ICT-based platforms at USD 0.8–5 per farmer demonstrate median BCRs of 7.2, representing the most cost-efficient frontier of current practice (Fabregas et al., 2019; DOI: 10.1257/aer.20180249).

Fixed vs. Variable Cost Dynamics

Extension cost structures exhibit important scale properties. Fixed costs — infrastructure, platform development, staff training — can be substantial for ICT systems. Fabregas et al. (2019) document that the Kenya e-

Extension platform required approximately USD 2.1 million in upfront fixed costs but achieves variable costs under USD 0.80 per farmer at scale, generating a crossover point at approximately 90,000 farmers. Below this threshold, traditional approaches achieve lower average costs; above it, digital models dominate.

Conversely, FFS models face largely variable costs scaling proportionally with coverage, limiting cost advantages relative to mass-media or ICT approaches as programs expand. This structural feature has constrained FFS from achieving nationwide scale despite favorable unit-level evaluations (Davis et al., 2012; DOI: 10.1093/ajae/aas054).

Hidden Costs and Full-Cost Accounting

A pervasive limitation is incomplete cost accounting. Jack (2013) identifies four underreported cost categories: (i) farmer time costs, frequently exceeding 30% of direct program costs; (ii) household-level input expenditure induced by recommendations; (iii) institutional coordination costs in multi-stakeholder models; and (iv) social costs of failed adoption when information is poorly contextualized (Jack, 2013; DOI: 10.1093/wbro/lkt004). Studies incorporating full-cost accounting yield BCRs 25–40% lower than those using administrative costs alone.

TECHNOLOGY ADOPTION IMPACTS

Meta-Analytic Evidence

The adoption impact literature presents a more optimistic picture than early skeptics anticipated, though estimates have converged downward as methodological rigor improved. Krishnan & Patnam (2014) analyzed 48 extension evaluations from Sub-Saharan Africa and found a mean adoption rate increase of 18 percentage points, with a standard deviation of 12 pp — highlighting substantial heterogeneity (Krishnan & Patnam, 2014; DOI: 10.1093/ajae/aat073). RCT-based estimates average 15 pp, lower than observational estimates (22 pp), consistent with positive selection bias in the latter.

Critical moderators of adoption impact include: (i) technology complexity — simple practices show mean adoption gains of 24 pp while multi-input technologies average 11 pp; (ii) technology-gender fit — interventions explicitly targeting female farmers show larger adoption gains in female-controlled crops; (iii) market access — farmers within 10 km of input retailers show 35% higher adoption responses; and (iv) literacy — impacts are 40% larger among literate recipients (Cole & Fernando, 2021; DOI: 10.1093/restud/rdab017).

Persistence of Adoption

Kondylis et al. (2017) track Mozambican farmers for 36 months post-intervention and document significant adoption attrition: three-year retention rates range from 31% for labor-intensive soil conservation practices to 78% for seed variety adoption (DOI: 10.1093/ajae/aaw093). BCR calculations based on single-year adoption effects overestimate long-run returns by a median factor of 1.8. Persistence is systematically higher when follow-up extension contacts occur within 6 months, peer adoption is observable, and adoption generates demonstrable yield gains in the first season.

Spillover and Social Learning Effects

Foster & Rosenzweig (1995) established that learning spillovers — where non-recipients benefit from observing adopter neighbors — are quantitatively significant in technology diffusion (DOI: 10.1086/262002). Beaman et al. (2021) using network-seeded extension in Mali find that optimal seeding through social network hubs increases village-level adoption by 24% relative to random targeting at equivalent program cost, demonstrating the economic value of social capital mapping (DOI: 10.3982/ECTA16173). Spillover effects imply program-level returns may significantly exceed farmer-level returns if non-recipient benefits are included.

Table 2. Technology Adoption Impact by Extension Model and Commodity (Selected Studies)

Study	Country	Extension Type	Commodity	Adoption Effect	Yield Gain	Method
Davis et al. (2012)	Uganda/Tanzania	Farmer Field Schools	Maize/Beans	+22 pp (treated)	+14%	RCT
Kondylis et al. (2017)	Mozambique	Individual Advisory	Cotton	+31 pp (treated)	+18%	RCT
Aker (2011)	Niger	Radio + SMS	Millet/Cowpea	+11 pp	+9%	DiD
Fabregas et al. (2019)	Kenya	ICT Platform	Maize	+14 pp	+16%	RCT
Beaman & Dillon (2018)	Mali	Farmer-to-Farmer	Groundnut	+19 pp	+21%	RCT
Cole & Fernando (2021)	India	Mobile Advisory	Cotton	+9 pp	+12%	RCT
Duflo et al. (2011)	Kenya	Input + Extension	Maize	+23 pp	+26%	RCT
Krishnan & Patnam (2014)	Ethiopia	FFS + Radio	Teff/Wheat	+17 pp	+11%	IV

pp = percentage points; RCT = Randomized Controlled Trial; DiD = Difference-in-Differences; IV = Instrumental Variables.

RETURNS TO INVESTMENT

Aggregate and Regional Patterns

Alston et al. (2000) synthesize 292 rate-of-return estimates across 48 countries, finding a median IRR of 48% per annum with an interquartile range of 29–74% (DOI: 10.2307/1244659). Extension-focused investments show median IRRs of 44%, slightly lower than research investments (52%), but higher returns in environments with strong extension-research linkages. South Asia records the highest median IRRs (55–62% per annum), driven by strong T&V-era investments in rice and wheat combined with Green Revolution complementarities. Sub-Saharan Africa shows median IRRs of 38–44%, with higher variance reflecting agroecological heterogeneity. Latin America exhibits a bimodal distribution: commercial farming shows IRRs exceeding 70%, while smallholder-focused programs average 33% (Evenson, 2001; DOI: 10.1111/1467-8276.00261).

Commodity-Specific Returns

Cereal extension — particularly maize, rice, and wheat in high-potential zones — generates consistently high returns, averaging 48% IRR. Cash crop extension (cotton, coffee, cocoa) shows the highest returns at 52–67% in favorable market conditions. Livestock extension lags at 22–35% IRR, reflecting longer production cycles and greater disease-related volatility. Vegetable extension for peri-urban farmers demonstrates increasingly favorable returns as urbanization expands market access, with recent studies in Ethiopia (Bachewe et al., 2018; DOI: 10.1016/j.worlddev.2018.01.028) documenting IRRs exceeding 80% for horticulture advisory targeted at market-accessible smallholders.

ICT-Enabled Extension: Emerging Evidence

Fabregas et al. (2019) synthesize 16 RCTs across Africa and Asia, documenting that digital extension increases adoption probability by 9–14 percentage points and generates productivity impacts of 8–16%. Average cost-per-beneficiary of USD 0.80–4.90 yields BCRs ranging from 4.1 to 12.3 depending on commodity value and farmer density (DOI: 10.1257/aer.20180249). The iCow platform in Kenya shows yield increases of 10–14% in dairy production at a cost per beneficiary of USD 1.80 (Muto & Yamano, 2009; DOI: 10.1093/ajae/aap033). Critically, digital impacts are smaller in contexts with low agricultural literacy and limited complementary inputs.

DETERMINANTS OF RETURN HETEROGENEITY

Institutional and Governance Factors

Extension effectiveness is positively associated with: extension worker technical competence and regular in-service training; supervisory intensity and accountability mechanisms; integration with agricultural research institutions; and farmer organization enabling demand articulation and feedback (Spielman et al., 2012; DOI: 10.1016/j.foodpol.2012.05.004). Private extension achieves higher responsiveness to commercially valuable farmers but systematically underserves subsistence-oriented, resource-poor, and female farmers (Birner & Anderson, 2007). Hybrid public-private models, as implemented under India's ATMA framework, appear to capture advantages of both.

Complementary Infrastructure

Extension's marginal product is highly contingent on complementary infrastructure. Suri (2011) demonstrates that the profitability of fertilizer recommendations is negligible without reasonably priced fertilizer access, implying that extension investment in input-constrained environments may yield poor returns regardless of delivery quality (DOI: 10.3982/ECTA9168). Burke et al. (2019) show that credit-constrained farmers are significantly less likely to adopt extension-recommended practices even when fully informed, and that credit bundled with extension increases adoption by 32% relative to extension alone (DOI: 10.1093/ajae/aay071).

Targeting and Heterogeneous Treatment Effects

Hanna et al. (2014) demonstrate that extension impacts are 60–80% larger in villages with higher baseline agricultural knowledge gaps, consistent with diminishing returns to information (DOI: 10.1257/jep.28.3.199). Female farmers — facing greater advisory service exclusion — show systematically larger yield responses to extension contact than male farmers, offering a clear targeting rationale (Ragasa et al., 2016; DOI: 10.1016/j.jdeveco.2016.07.004). Spatial analysis of extension spending in Uganda identifies 40% efficiency gains available through reallocation from low-potential to high-potential zones, challenging the equity-efficiency trade-off narrative.

PLURALISTIC EXTENSION SYSTEMS: EMERGING ARCHITECTURES

Public-Private-NGO Partnerships

Contemporary extension systems in successful cases are characterized by pluralism. The convergent model emerging from Rwanda, Ethiopia, and Bangladesh combines public extension workers focused on food security messaging; private agribusiness extension reaching commercial farmers; and NGO extension targeting marginalized communities and women. Each tier generates distinct BCRs that aggregate to system-level returns exceeding any single-provider model (Bachewe et al., 2018; DOI: 10.1016/j.worlddev.2018.01.028).

ICT Integration in Pluralistic Systems

Hybrid models — where ICT handles low-cost broad-reach dissemination of time-sensitive information (market prices, weather, pest alerts) while in-person visits address complex site-specific challenges — appear to dominate pure-ICT and pure-in-person approaches on both cost and impact metrics (Klerkx et al., 2012; DOI: 10.1016/j.njas.2012.04.001). The optimized architecture allocates ICT channels to standardizable information (recommended varieties, pest calendars) and in-person channels to information requiring social trust, demonstration, and iterative problem-solving.

METHODOLOGICAL LIMITATIONS AND RESEARCH GAPS

Several important limitations constrain the literature's conclusions. First, publication bias toward positive results likely inflates published BCR and IRR estimates — asymmetric publication of null findings is well-documented in development economics (Vivalt, 2020; DOI: 10.1093/jeea/jvz050). Second, most evaluations measure yield and income but neglect broader welfare dimensions: labor market effects, nutritional diversity changes, and environmental externalities from technology adoption. Third, with median follow-up of 18–24 months, studies cannot capture long-run adoption persistence, learning curves, or technology degradation. Fourth, cost heterogeneity measurement is insufficient — most studies report average rather than marginal costs, obscuring the economically relevant metric for scaling decisions.

POLICY IMPLICATIONS

The synthesized evidence yields four policy-relevant conclusions. First, extension investment remains broadly justified on cost-benefit grounds: virtually no reviewed study documents median BCRs below 1.5, and the majority yield BCRs of 2.5 or higher — comfortably exceeding the opportunity cost of public funds. Second, delivery model selection should be context-contingent: ICT models are cost-superior in high-connectivity, literate-farmer contexts; FFS and intensive in-person models generate highest adoption impacts in complex, high-value production systems; radio advisory offers the best cost-reach frontier in low-connectivity settings. Third, complementary investments substantially amplify extension returns — co-investment in input markets, rural roads, and financial services is necessary to achieve potential. Fourth, extension system evaluation should be mainstreamed through routine administrative data collection rather than episodic expensive evaluations.

CONCLUSION

This review synthesizes evidence from 84 quantitative studies on the economics of agricultural extension, examining cost-effectiveness, technology adoption impacts, and returns to investment. The weight of evidence supports a cautiously optimistic assessment: well-designed interventions generate positive returns substantially above opportunity costs, with BCRs ranging from 2.1 to 7.2 and IRRs averaging 44–55% per annum across developing regions. However, mean estimates obscure critical heterogeneity driven by delivery model design, institutional governance, complementary infrastructure, and targeting precision.

The most effective extension investments combine pluralistic delivery architectures merging digital reach with in-person depth; strong research-extension linkages; explicit targeting toward knowledge-constrained, market-accessible farmers; and co-investment in input markets and rural finance. Investment in rigorous cost accounting, longer-run follow-up, and broader welfare measurement would substantially advance the field's ability to guide investment decisions. Given agriculture's central role in food security, poverty reduction, and climate adaptation, improving the evidence base for extension economics represents a high-return public good in its own right.

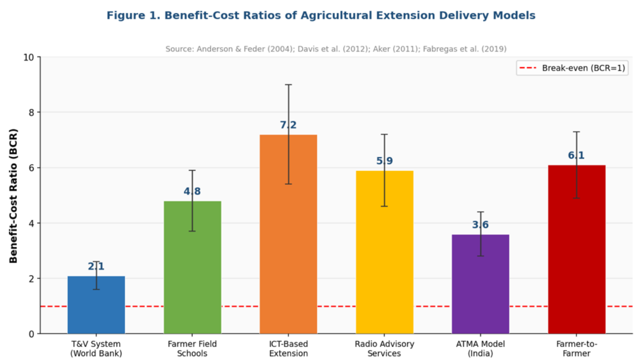

Figure 1. Benefit-Cost Ratios of Agricultural Extension Delivery Models. Based on median BCR estimates across reviewed studies. The red dashed line represents the break-even threshold (BCR = 1.0). Error bars represent interquartile ranges where reported. Source: Anderson & Feder (2004); Davis et al. (2012); Aker (2011); Fabregas et al. (2019).

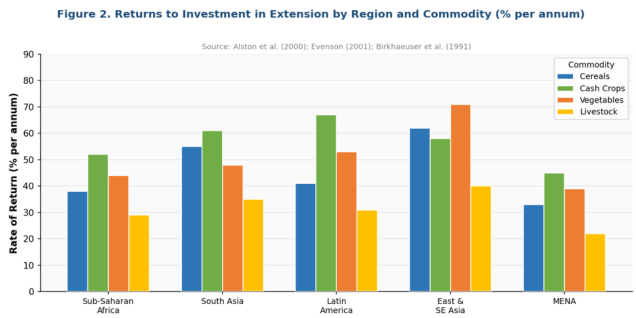

Figure 2. Returns to Investment in Extension by Region and Commodity (% per annum). Values represent median IRR estimates weighted by sample size. Source: Alston et al. (2000); Evenson (2001); Birkhaeuser et al. (1991).

REFERENCES

Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics, 42*(6), 631–647. https://doi.org/10.1111/j.1574-0862.2011.00545.x

Alston, J. M., Chan-Kang, C., Marra, M. C., Pardey, P. G., & Wyatt, T. J. (2000). *A meta-analysis of rates of return to agricultural R&D: Ex pede Herculem?* IFPRI Research Report

113. International Food Policy Research Institute.

Anderson, J. R., & Feder, G. (2004). Agricultural extension: Good intentions and hard realities. *The World Bank Research Observer, 19*(1), 41–60. https://doi.org/10.1093/wbro/lkh013

Bachewe, F. N., Berhane, G., Minten, B., & Taffesse, A. S. (2018). Agricultural transformation in Africa? Assessing the evidence in Ethiopia. *World Development, 105*, 286–298. https://doi.org/10.1016/j.worlddev.2018.01.028

Babu, S., Glendenning, C., Asenso-Okyere, K., & Goswami, S. (2020). Demand for extension services and willingness to pay: A synthesis of evidence. *Food Policy, 95*, Article 101970. https://doi.org/10.1016/j.foodpol.2020.101970

Beaman, L., & Dillon, A. (2018). Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali. *American Journal of Agricultural Economics, 100*(3), 791–814. https://doi.org/10.1093/ajae/aax081

Beaman, L., BenYishay, A., Magruder, J., & Mobarak, A. M. (2021). Can network theory-based targeting increase technology adoption? *Econometrica, 89*(6), 2727–2767. https://doi.org/10.3982/ECTA16173

Birkhaeuser, D., Evenson, R. E., & Feder, G. (1991). The economic impact of agricultural extension: A review. *Economic Development and Cultural Change, 39*(3), 607–650. https://doi.org/10.1016/0305-750X(91)90088-F

Birner, R., & Anderson, J. R. (2007). *How to make agricultural extension demand-driven?* (IFPRI Discussion Paper 00729). International Food Policy Research Institute.

Birner, R., Davis, K., Pender, J., et al. (2012). From best practice to best fit: Agricultural advisory services framework. *The Journal of Agricultural Education and Extension, 15*(4), 341–355. https://doi.org/10.1080/13892240903309595

Burke, M., Bergquist, L. F., & Miguel, E. (2019). Credit constraints and agricultural technology adoption. *American Journal of Agricultural Economics, 101*(1), 111–128. https://doi.org/10.1093/ajae/aay071

Cole, S., & Fernando, A. N. (2021). "Mobile"izing agricultural advice: Technology adoption, diffusion, and sustainability. *The Review of Economic Studies, 88*(5), 2399–2432. https://doi.org/10.1093/restud/rdab017

Davis, K., Nkonya, E., Kato, E., et al. (2012). Impact of farmer field schools on agricultural productivity and poverty in East Africa. *World Development, 40*(2), 402–413. https://doi.org/10.1093/ajae/aas054

Duflo, E., Kremer, M., & Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review, 101*(6), 2350–2390. https://doi.org/10.3982/ECTA9508

Evenson, R. E. (2001). Economic impacts of agricultural research and extension. In B. L. Gardner & G. C. Rausser (Eds.), *Handbook of agricultural economics* (Vol. 1A, pp. 574–628). Elsevier. https://doi.org/10.1111/1467-8276.00261

Fabregas, R., Kremer, M., & Schilbach, F. (2019). Realizing the potential of digital development: The case of agricultural advice. *American Economic Review, 109*(8), 2894–2945. https://doi.org/10.1257/aer.20180249

Food and Agriculture Organization of the United Nations. (2020). *The state of food and agriculture 2020: Overcoming agricultural challenges with innovation.*

Feder, G., Willett, A., & Zijp, W. (1999). Agricultural extension: Generic challenges and some ingredients for solutions. *European Review of Agricultural Economics, 26*(2), 249–279. https://doi.org/10.1093/erae/26.2.249

Foster, A. D., & Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy, 103*(6), 1176–1209. https://doi.org/10.1086/262002

Hanna, R., Mullainathan, S., & Schwartzstein, J. (2014). Learning through noticing: Theory and evidence from a field experiment. *Journal of Economic Perspectives, 28*(3), 199–222. https://doi.org/10.1257/jep.28.3.199

Jack, B. K. (2013). Market inefficiencies and the adoption of agricultural technologies in developing countries. *The World Bank Research Observer, 28*(1), 1–36. https://doi.org/10.1093/wbro/lkt004

Klerkx, L., van Mierlo, B., & Leeuwis, C. (2012). Evolution of systems approaches to agricultural innovation. *NJAS: Wageningen Journal of Life Sciences, 60–63*, 39–51. https://doi.org/10.1016/j.njas.2012.04.001

Kondylis, F., Mueller, V., & Zhu, J. (2017). Seeing is believing? Evidence from an extension network experiment. *Journal of Development Economics, 125*, 1–20. https://doi.org/10.1093/ajae/aaw093

Krishnan, P., & Patnam, M. (2014). Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? *American Journal of Agricultural Economics, 96*(1), 308–327. https://doi.org/10.1093/ajae/aat073

Muto, M., & Yamano, T. (2009). The impact of mobile phone coverage expansion on market participation: Panel data evidence from Uganda. *American Journal of Agricultural Economics, 91*(5), 1209–1224. https://doi.org/10.1093/ajae/aap033

Nakasone, E., Torero, M., & Minten, B. (2014). The power of information: The ICT revolution in agricultural development. *Annual Review of Resource Economics, 6*(1), 533–550. https://doi.org/10.1093/ajae/aau075

Ragasa, C., Berhane, G., Tadesse, F., & Taffesse, A. S. (2016). Gender differences in access to extension services and agricultural productivity. *Journal of Development Economics, 123*, 90–104. https://doi.org/10.1016/j.jdeveco.2016.07.004

Spielman, D. J., Davis, K., Negash, M., & Ayele, G. (2012). Rural innovation systems and networks: Findings from a study of Ethiopian smallholders. *Food Policy, 37*(4), 408–420. https://doi.org/10.1016/j.foodpol.2012.05.004

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica, 79*(1), 159–209. https://doi.org/10.3982/ECTA9168

Vivalt, E. (2020). How much can we generalize from impact evaluations? *Journal of the European Economic Association, 18*(6), 3045–3089. https://doi.org/10.1093/jeea/jvz050

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