

Trac(k)tors of Change: Monitoring, Tractor Mobility and Agricultural Mechanization in Kenya

Sophie Nottmeyer

CEMFI

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Lack of Technology Adoption

- Low agricultural productivity in Africa
- Limited adoption of modern technologies, e.g. mechanization
 - Credit constraints, small scale of production (Foster & Rosenzweig 2022)
- **Rental markets** could overcome capital indivisibilities (Bassi et al 2022)
 - Yet remain thin or absent in rural areas, even where returns are high

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 - Yet remain thin or absent in rural areas, even where returns are high
- **This paper:** *supply-side* monitoring frictions limit spatial allocation

Monitoring Problem on Private Tractor Rental Markets

- Delegated operation of capital
 - Private individuals (\neq farmers) invest in tractors to rent them out
 - Owners hire an operator to drive tractor to farmers' fields
- Informal revenue sharing agreement
 - Owners set general area and target price (per acre)
 - Operators searches for customers and collects payments on the spot
 - Keeps a fixed share of revenue and returns the rest
- Owner-operator **moral hazard**
 - Owner (principal) does not observe actions of operator (agent)
 - ▶ Examples: underreport number and size of jobs, overstate distance, misuse fuel, drive carelessly, take shortcuts on poor roads, ...
- Similar to other sectors (e.g. trucking, ride-hailing, public transportation)

Spatial Implications

- Owners restrict set of locations where tractors can work
- Traditional monitoring more costly at a distance
 - Keep tractors close to home or where they can rely on personal network
 - ▶ Examples: unannounced field visits, check-and-call-system, fuel consumption checks
- Why this matters for spatial scope and efficiency
 1. **Spatial mismatch**: owners are often based in cities \neq where tractors are most needed or productive
 2. **Seasonality**: tractors are needed in different regions at different times

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→ **Research Question**: How important are these monitoring frictions for the spatial allocation of tractor services? What are the consequences for agricultural productivity?

This Paper

- Leverage the **introduction of a GPS tracking app** for tractors in Kenya
 - Reduces information asymmetry
 - Unique, georeferenced data on tractor use
 - ▶ About 1,200 tractors and nearly one million serviced fields 2018-2025
- Provide **empirical evidence** on the effects of digital monitoring
 - Exploit panel dimension to document changes in location choices after adoption
 - Combine with **satellite data** to assess impact on agricultural productivity using a matching event study design
- Develop **spatial model** to quantify aggregate gains
 - Moving costs depend on owners ability to monitor operators remotely
 - Calibrated with tractor GPS data using revealed preference approach

Preview of Results

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 - ... expand their range of operation
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- Fields visited by monitored tractors experience a larger increase in vegetation growth than similar nearby fields
→ suggesting productivity gains at destination
- Counterfactual analysis: removing monitoring friction
 - Increases aggregate output by around 2%
 - Reduces spatial misallocation of tractor services by about 15%

Literature and Contribution

- **Barriers to agricultural technology adoption and mechanization**
(Suri & Udry 2024; Aggarwal et al 2024; Caunedo & Kala 2022; Caunedo et al 2022)
 - Focus on *supply-side* friction that shape access to key input market across space
 - Novel data on tractor utilization
- **Misallocation and capital rental markets**
(Hsieh & Klenow 2009; Restuccia & Rogerson 2017; Bassi et al 2022)
 - Focus on spatial frictions, when capital needs to move
- **Monitoring and firm performance**
(Hubbard 2000, 2003; Kelley et al 2024)
 - Improvements through location choice
 - Link firm-level monitoring problem to market efficiency
- **Spatial mobility in developing countries**
(Bryan et al 2025; Kreindler & Miyauchi 2023; Blanchard et al 2025; Kreindler et al 2025)
 - Use *GPS tracking data* and spatial model to study *capital* mobility

Roadmap

Intro

Context & Data

Empirical Analysis

Model

Conclusion

Agricultural Mechanization in Kenya

- Agriculture is a key sector in the economy
 - Accounts for 21% of GDP and 34% of total employment (WDI 2019)
 - 46% of households engage in crop farming (Census 2019)
 - Dominated by small, fragmented farms (median size = 1 acre)

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 - Mechanization rates are persistently low
 - Less than 1% of households own a tractor (Census 2019)
 - ▶ 43% do not engage in agricultural production
 - ▶ 33% reside in urban areas
 - Around 18% of cultivated land in East Africa is prepared using tractors
 - ▶ Alternatives: 50% manual, 32% animal (Mrema et al 2018)
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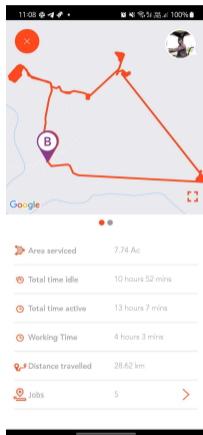
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→ Farmers rely on private tractor rental markets to mechanize
- Tractors are an established technology with well-understood returns
- Anecdotal evidence: monitoring problem as a major challenge for tractor owners
 - *“You are the servant, they are the boss. You own the tractor, but they make more money than you.”*

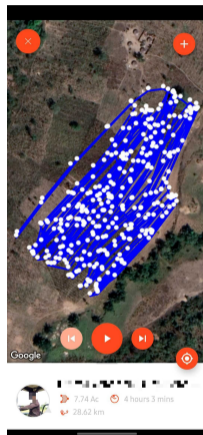
New Monitoring Technology

- Introduced by local start-up **Hello Tractor (HT)** in 2018
 - Owners pay installation fee & annual subscription
 - Rapid adoption → 2-8% of all tractors in Kenya (Census 2019; FAOSTAT 2008)
- Components:
 1. **GPS tracking device:**
 - ▶ Mounted inside tractor in unknown location
 - ▶ Sends real-time location pings, including when tractor is idle
 - ▶ Internal battery and offline data storage
 2. **Mobile & web app:**
 - ▶ Showcases information sent by device
 - ▶ Accessed only by the owner

Tractor Owner Application



(a) Daily Activity Report



(b) Track Replay

Data

Tractor GPS data from HT (2018-2025)

- Activity records
 - 'Job' = work area boundary including timestamp & unique tractor ID
 - All 917,479 jobs from 1,225 unique tractors
- Inferred home locations
 - Ward with highest share of pings at night (12-5am EAT)
 - Available for 88% of tractors (96% of jobs)
- Limited tractor characteristics (incl. owner information)

[Summary Stats](#)[Activity Growth](#)

Population and Housing Census (2019)

- Household tractor ownership at the county level

[Sample Comparison](#)

Data

Fieldwork

- Tractor owner interviews and focus group discussion
- Farmer survey in Kakamega County (N=415)
 - Sample includes both HT and non-HT farmers
 - Agricultural production, tractor use, GPS plot boundaries

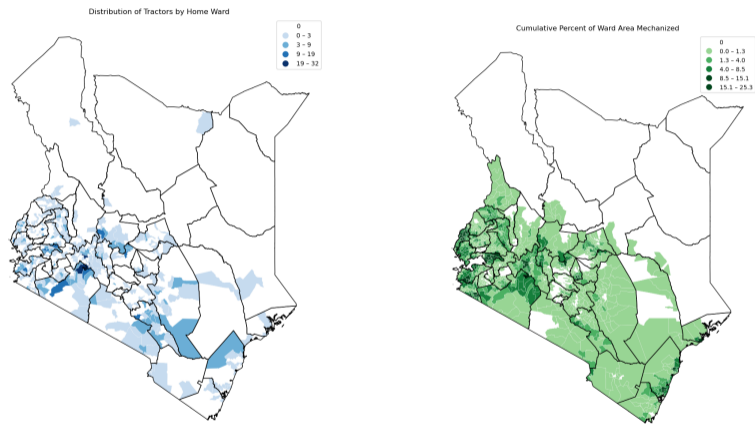
Data

Spatial data

- Potential yields
 - FAO GAEZ v4, 9km resolution
 - Yield predictions based on exogenous location characteristics (e.g. weather, soil), under different input scenarios
 - **Marginal returns to mechanization**: $\Delta Y_c = Y_c(High) - Y_c(Low)$
- Satellite imagery (2017-2024)
 - Sentinel-2 mission, 10m resolution
 - **Proxy for agricultural productivity at destination**
- Other (e.g. admin boundaries, cropland area, elevation)

[More](#)

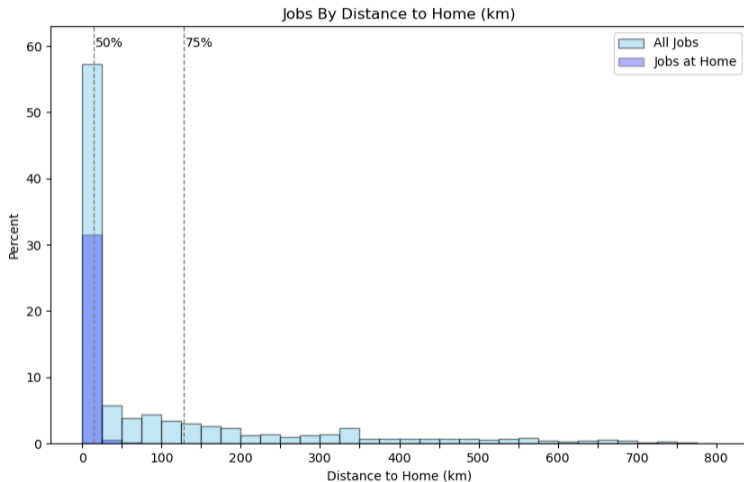
Spatial Coverage of HT Data



Note: Map of counties, number of tractors (left) and cumulative share of area mechanized (right) at ward level.

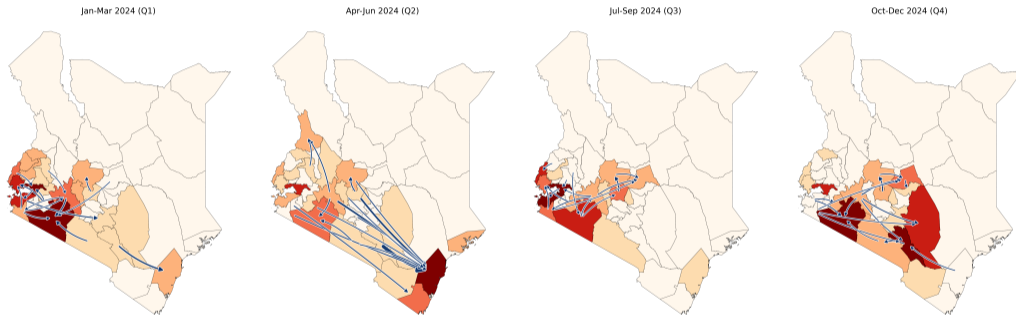
Expansion

Distance to Home Matters for Job Location



Note: Histogram of the share of jobs by distance to home (straightline distance between job and home ward centroid) in 25km bins.

Seasonality



Note: HT tractor activity data for 2024. Map of counties, shading indicates share in total jobs in each quarter and arrows represent top 10 flows between counties (jobs serviced by tractors from a different county).

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How Tractor Mobility Patterns Change After Adoption

- **Assumption:** tractors will initially behave similarly to before adoption
 - Incentives take time to adjust to better monitoring (Hubbard 2003, Kelley et al 2024)

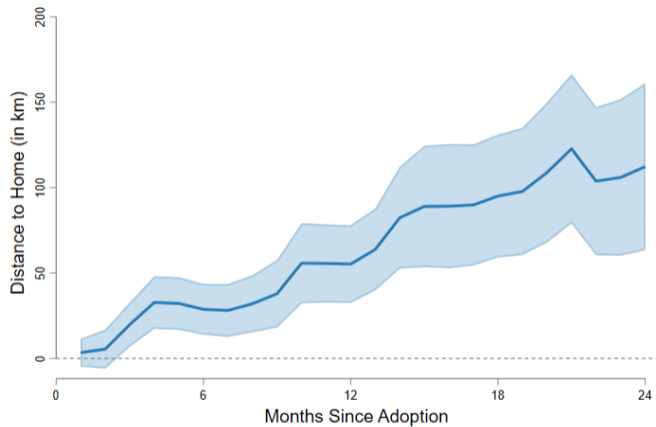
- Within-tractor estimation:

$$\text{Distance}_{it} = \alpha_i + \alpha_{my(t)} + \sum_{k>0} \beta_k e_{it}^k + \varepsilon_{it} \quad (1)$$

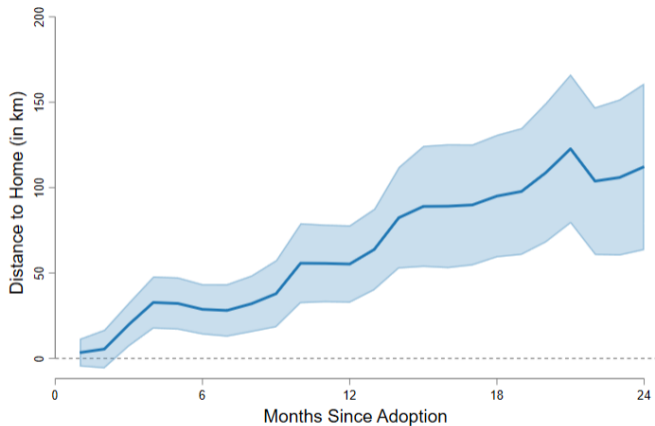
- Distance_{it} : average distance to home of tractor i to jobs serviced on day t
- e_{it}^k : dummy for k -th month since adoption
- α_i : tractor fixed effects
- $\alpha_{my(t)}$: month-year fixed effects
- Coefficients of interest: β^k change in distance to home k months after adoption compared to the first month of monitoring

Data Example

Monitored Tractors Gradually Operate Farther Away



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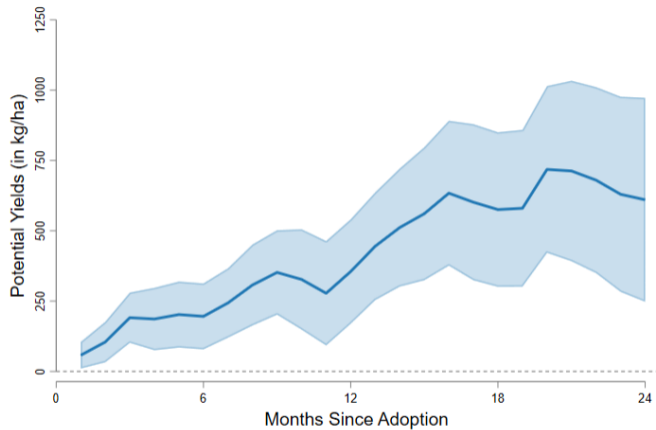


→ consistent with reduction in monitoring friction

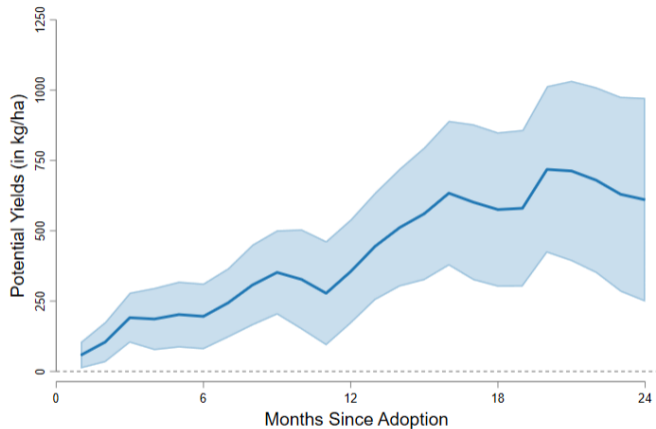
By Cohort

More

... & where Marginal Returns to Mechanization Are Higher



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→ suggests more efficient spatial allocation

More

Does Monitoring Make a Difference for Agricultural Productivity?

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Empirical challenges:

1. No granular output data
2. No counterfactual

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- ▶ Normalized Difference Vegetation Index (NDVI) = $\frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$
- ▶ Within-season 'greenup': $\Delta\text{NDVI} = \text{Peak} - \text{Start}$

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Does Monitoring Make a Difference for Agricultural Productivity?

Manual

2024-03-06, NDVI=0.46



2024-05-30, NDVI=0.77



$\Delta\text{NDVI}=0.31$
Yield=186.48kg/acre

Tractor

2024-03-06, NDVI=0.30



2024-05-30, NDVI=0.85



$\Delta\text{NDVI}=0.55$
Yield=1678.18kg/acre

Note: Illustration of productivity proxy using fields from farmer survey in Butere sub-county.

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- Solution: construct comparison fields using **matching** procedure
 - ▶ Select jobs Jan-April (land preparation), first visit only
 - ▶ One-to-one match: proximity, cropland probability, size, $\Delta NDVI$ pre-trend

Algorithm

Does Monitoring Make a Difference for Agricultural Productivity?



Note: Example HT job (left) with matched control (right).

→ $N=33,256$ pairs of treated and control fields

Raw Data Means

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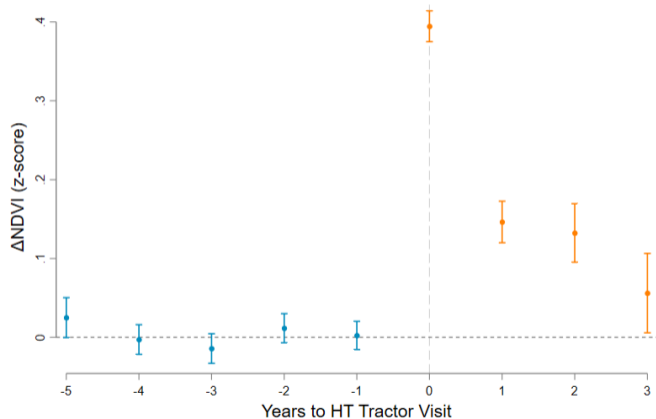
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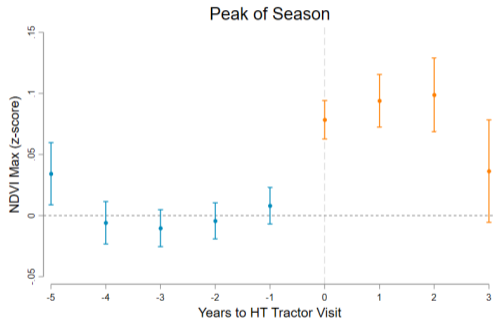
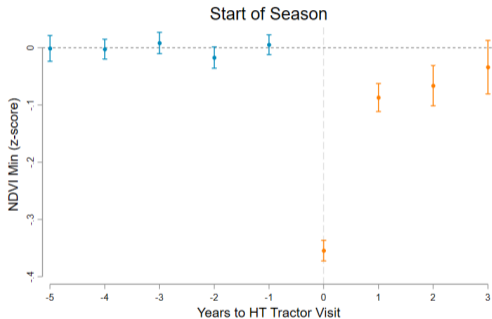
Algorithm

- Estimate event study on within-pair difference (Callaway and Sant'Anna, 2021)
 - Control may have mechanized → lower bound effect

Tractor Visits Increase Field-Level Productivity



More Effective Land Preparation, Better Vegetation Growth



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Quantitative Spatial Model

- **Goal:** quantify aggregate gains from monitoring
 - Counterfactual tractor allocation
 - Equilibrium effects
- Economy with $j = 1, \dots, J$ locations
- **Tractors:**
 - Fixed stock \bar{T}
 - Initial distribution $T_{-1,h}$
 - Owners Ω choose where to send tractors given home location $h \in J$
- **Farmers:**
 - Representative farmer in each location
 - Produce homogenous, freely traded good
 - Choose how much tractor services to hire
- **Equilibrium:** returns r_j such that tractor supply equals demand in every location j

Tractor Location Choice

Tractor owner ω chooses where to send tractor given home location h :

$$\max_{j \in J} V_{j|h}(\omega) = \frac{r_j}{c_{hj}} z_j(\omega) \quad (2)$$

where

- r_j : return of sending tractor to j
- $c_{hj} = D_{hj}^\kappa$: cost of moving between h and j
 - D_{hj} : bilateral distance
 - $\kappa = \kappa^T + \kappa^M$: **distance elasticity of moving cost**
 - ▶ κ^T : transport
 - ▶ κ^M : owners' ability to monitor operator and align incentives; digital monitoring: $\downarrow \kappa^M$
- $z_j(\omega)$: idiosyncratic **productivity** draw
 - e.g. personal networks, local knowledge about demand, etc.
 - $z \sim F(z) = \exp(-z^{-\theta})$

Tractor Location Choice

The **probability** of a tractor from h working in j is: (Eaton & Kortum, 2002)

$$\pi_{j|h} \equiv Pr \left[\frac{r_j}{c_{hj}} z_j > \max_{j' \neq j} \frac{r_{j'}}{c_{hj'}} z_{j'} \right] = \frac{(r_j/c_{hj})^\theta}{\sum_s (r_s/c_{hs})^\theta} = \frac{(r_j/c_{hj})^\theta}{\Phi_h} \quad (3)$$

Then, the **supply of tractors** in j is given by:

$$T_j = \sum_h \pi_{j|h} T_{-1,h} = \sum_h \frac{(r_j/c_{hj})^\theta}{\Phi_h} T_{-1,h} \quad (4)$$

Taking logs of (3) yields the **gravity equation**:

$$\log \pi_{j|h} = \theta \log r_j - \theta \kappa \log D_{hj} - \log \Phi_h \quad (5)$$

Parameter Estimation

- Estimate gravity equation using pooled bilateral job flows and distances:

$$\log \pi_{j|h} = \alpha_j + \beta \log D_{j|h} + \alpha_h + \eta_{j|h} \quad (6)$$

→ Identifies elasticity bundle $\beta = -\theta\kappa$

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→ Identifies elasticity bundle $\beta = -\theta\kappa$

- How to disentangle?
 - Previous literature: match variance of Fréchet (Ahlfehldt et al, 2015) → arbitrary, noisy
 - **New approach**: use **exogenous demand shifter** to estimate θ directly

$$\hat{\alpha}_j = \gamma_0 + \theta \log \tilde{r}_j + X_j + \varepsilon_j \quad (7)$$

- ▶ $\hat{\alpha}_j$: estimated destination FE from pooled gravity
- ▶ \tilde{r}_j : potential yields (FAO GAEZ v4)
- ▶ X_j : controls (terrain ruggedness, wealth, population, area)

→ $\kappa = -\beta/\theta$

Parameter Estimation

Pooled Gravity Estimation		
	(1)	(2)
	PPML	OLS
Log(Distance)	-1.295*** (0.035)	
Log(Potential Yields)		0.684*** (0.204)
Controls		Yes
Obs.	401,388	986
Pseudo R ²	0.69	
R ²		0.40

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$$\rightarrow \hat{\theta} = 0.684, \hat{k} = \frac{1.295}{\hat{\theta}} = 1.893$$

Farmer Demand and Model Solution

- Cobb-Douglas production function ($\gamma < 1$):

$$Y_j = A_j \bar{H}_j^{1-\gamma} T_j^\gamma \quad (8)$$

- A_j : exogenous location productivity (e.g. soil)
- \bar{H}_j : fixed land endowment
- T_j : tractor services

- Profit maximization over T_j yields downward-sloping demand:

$$r_j = \gamma A_j \left(\frac{T_j}{\bar{H}_j} \right)^{\gamma-1} \quad (9)$$

- Calibrate γ as tractor rental cost share from own farmer survey $\rightarrow \hat{\gamma} = 0.14$
- Solve initial equilibrium to back out A_j given data $(T_j, T_{-1,h}, \bar{H}_j)$ and $\hat{\kappa}$

Estimating Shifter in κ

- Comparative statics exercise: changes in κ
 - Use empirical within-tractor variation for identification (again)
- Re-estimate gravity equation at the tractor level, allowing $\beta(\tau)$:

$$\log \pi_{j|h(i),t} = \alpha_i + \alpha_{jt} + \beta_0 \log D_{j|h(i)} + \beta_1 \tau_{it} \times \log D_{j|h(i)} + \eta_{j|h(i),t}$$

where

- $\log \pi_{j|h(i),t}$: job flow of tractor i based in h to j in month t
- τ_{it} : months since adoption
- α_i : tractor fixed effects
- α_{jt} : destination-month fixed effects

Estimating Shifter in κ

- Results:

Tractor-Level Gravity Estimation	
(1)	
PPML	
Log(Distance)	-1.32989*** (0.03201)
Log(Distance) $\times \tau$	0.00233*** (0.00090)
Obs.	10,739,033
Pseudo R ²	0.54

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

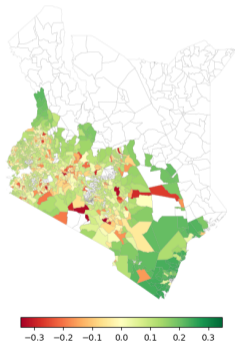
$$\rightarrow \hat{\kappa}_0 = \frac{1.322}{\hat{\theta}} = 1.944, \quad \frac{d\hat{\kappa}}{d\tau} = \frac{-0.00233}{\hat{\theta}} = -0.0034$$

- Values for counterfactual simulations:
 - At entry baseline: $\kappa = \hat{\kappa}_0 = 1.944$
 - After five years of monitoring: $\kappa' = \hat{\kappa}_0 + d\hat{\kappa}/d\tau \times 60 = 1.74$
- \rightarrow redistribute tractor jobs, everything else equal

Removing Monitoring-Related Spatial Frictions

- Tractors move away from home and towards more productive locations
 - Agricultural output ($\% \Delta \sum_j Y_j$) increases by 2.18%
 - Spatial misallocation ($\% \Delta \sigma(\partial Y_j / \partial T_j)$) decreases by 15.9%

Log Changes in T_j



Rollout to All Tractors

- Census sample
 - Number of households owning a tractor at the county level (N=7,093, 10% sample)
 - Weight by average number of jobs per tractor in HT data
 - Disaggregate into wards using within-county HT distribution $\rightarrow T_{-1,h}^{agg}$
- Counterfactual simulations as before:
 - Aggregate output increases by 1.3%
 - Spatial misallocation decreases by 9%
 \rightarrow smaller effects due to broader initial distribution
- Caveats:
 - Only includes locations with tractor activity in HT data (A_j available)
 - Includes HT tractors
 - Assigning average utilization levels

Cost Comparison with Equivalent Fuel Subsidy

- Alternative policy to encourage tractors to travel farther: fuel subsidy
- Keeping monitoring friction fixed at baseline $\kappa = \hat{\kappa}_0$
- Calibrate reduction in c_{hj} needed to achieve same efficiency gains
 - $c'_{hj} = (D_{hj}(1-x))_0^{\kappa} \rightarrow x = 0.71$ per km
 - Fuel constitutes around 70% of variable transport cost \rightarrow fully subsidize
- Total cost comparison:
 - Fuel subsidy: $\$1.05 \times \sum(\pi'_{j|h} T_{-1,h}^{agg} D_{hj}) = \9.3 billion
 - Digital monitoring: $70,930 \times (\$125 + 5 \times \$60) = \$0.03$ billion

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- Reducing monitoring frictions on the **supply-side** of rental markets can improve the spatial allocation capital and increase (aggregate) productivity
- Policy implications:
 - Not enough to invest in machinery, need to ensure efficient use
 - Digital technology as a cost-effective tool to improve farmers' access to mechanization services in remote areas
- External validity and relevance:
 - Many developing countries share similar features
 - Similar monitoring problems in other sectors → spatial choices and market efficiency
- Future work:
 - Endogenous entry (tractor investment)
 - Market structure and competition
 - Structural transformation

Thank You!

sophie.nottmeyer@cemfi.edu.es

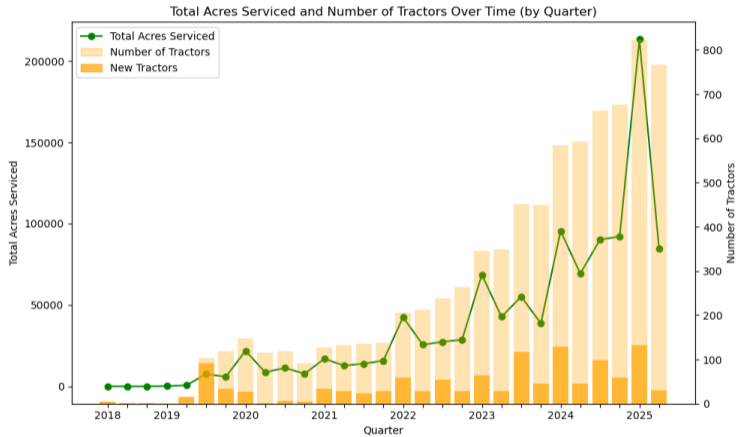
<https://sophienottmeyer.github.io/>

Summary Statistics

	N	Mean	Std	Min	25%	50%	75%	Max
Jobs								
Year	917,479	2023	1	2018	2023	2024	2024	2025
Size (acres)	917,479	1.20	2.23	0.00	0.27	0.63	1.29	155.14
Av. Potential Yield (kg/ha)	864,362	4,547.45	1160.42	-472.00	3,514.00	4,514.00	5606.00	7328.00
Distance to Home (km)	877,602	99.06	158.53	0.01	5.54	14.00	127.92	789.34
Tractors								
Days in Sample (in years)	1,225	1.52	1.34	0.00	0.46	1.20	2.20	5.92
Percent of Days Active	1,157	36.68	20.99	0.43	20.22	35.46	52.49	94.55
Total Acres per Year in Sample	1,225	726.40	702.49	0.18	256.14	545.26	989.10	6,593.50
Jobs per Day Active	1,225	3.90	1.61	1.00	2.82	3.80	4.76	20.67
Acres per Day Active	1,225	4.68	3.03	0.00	3.00	4.13	5.66	30.74
Assigned Home Ward Share of Nighttime Pings	1,078	66.93	25.87	11.00	44.00	69.00	93.00	100.00
Share of Jobs at Home	1,078	38.95	31.61	0.00	9.56	32.92	64.05	100.00
Av. Distance to Home (km)	1,078	68.74	95.47	0.92	8.44	23.74	89.34	554.34

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Growth in On-app Activity

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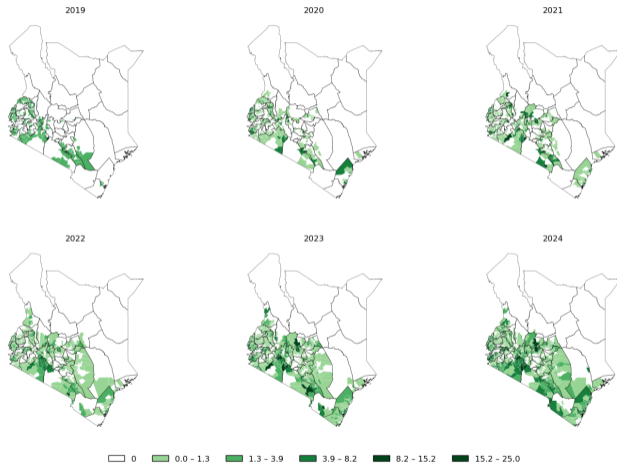
Other Spatial Data

- **Spatial units:** 47 counties, 1450 wards (median surface area 77km²); shapefiles from Humanitarian Data Exchange
- **Cropland area:** Digital Earth Africa 2019 Cropland Mask (> 70% probability)
- **Terrain ruggedness:** Terrain Ruggedness Index (TRI) calculated from Copernicus Digital Elevation Model
- **Population:** WorldPop (2018)
- **Wealth:** Relative Wealth Index (RWI) from Data for Good at Meta

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Geographic Expansion Over Time

Percent of Ward Cropland Area Mechanized Each Year



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Data Example

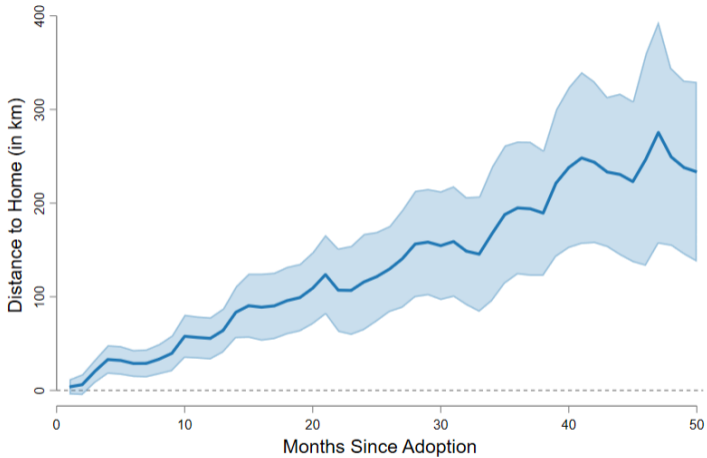
$$e_{it}^k = \mathbb{I}[\tau_{it} = k], \quad \tau_{it} = \lfloor (t - t_i^0)/30 \rfloor$$

i	t	t_i^0	$(t - t_i^0)$	τ_{it}	e_{it}^0	e_{it}^1	e_{it}^2	...
122122	2023-12-22	2023-12-22	1	0	1	0	0	...
122122	2024-01-14	2023-12-22	24	0	1	0	0	...
122122	2024-01-19	2023-12-22	29	0	1	0	0	...
122122	2024-01-29	2023-12-22	39	1	0	1	0	...
122122	2024-02-07	2023-12-22	48	1	0	1	0	...
...
122122	2024-02-19	2023-12-22	60	2	0	0	1	...

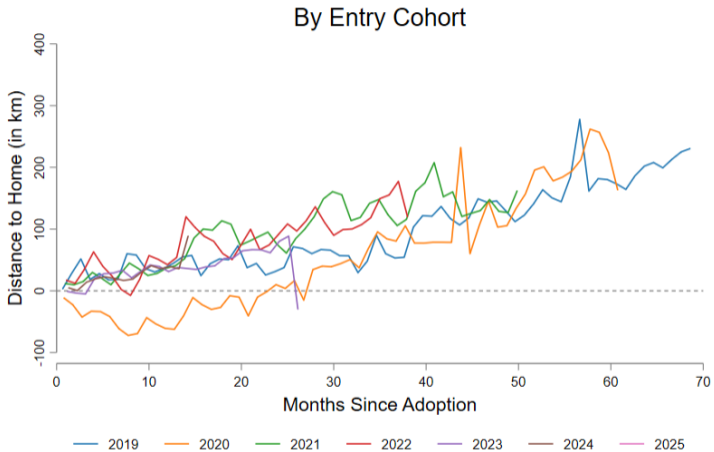
Robustness & Other Outcomes

1. All durations
2. Cohort analysis
3. Experienced tractor owners
4. High confidence home assignment
5. Propensity to work at home
6. Propensity to return home (trip chaining)
7. Propensity to be active
8. Number of jobs per day

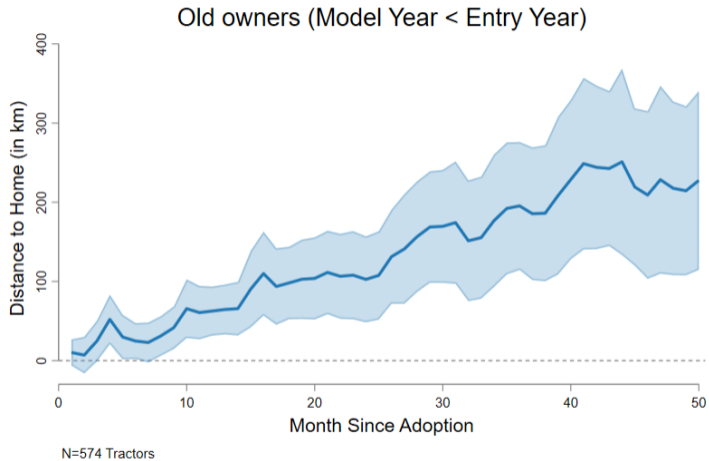
All Durations

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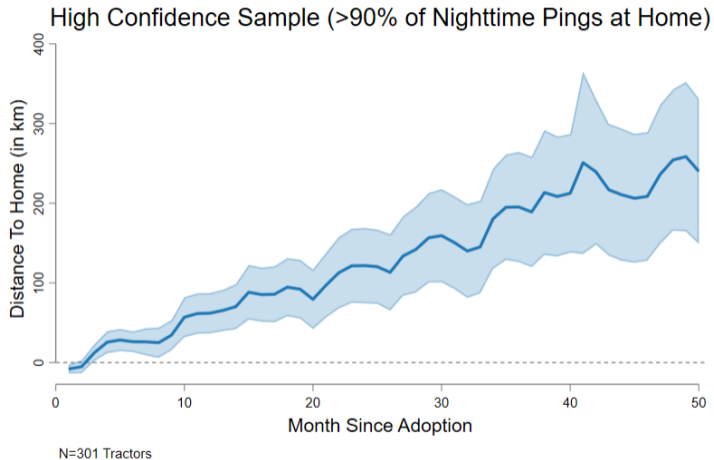
Cohort Analysis

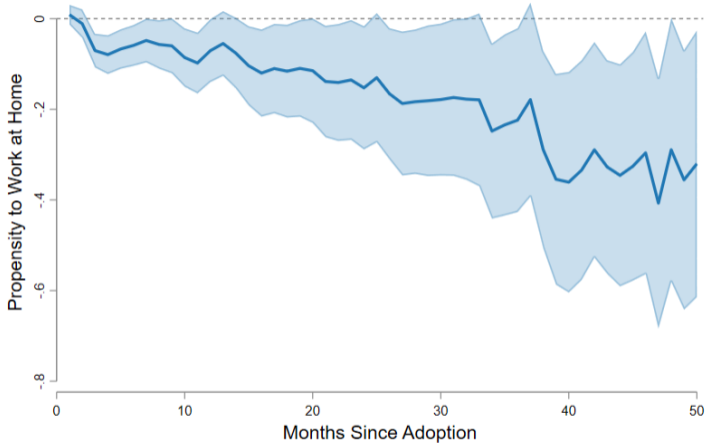
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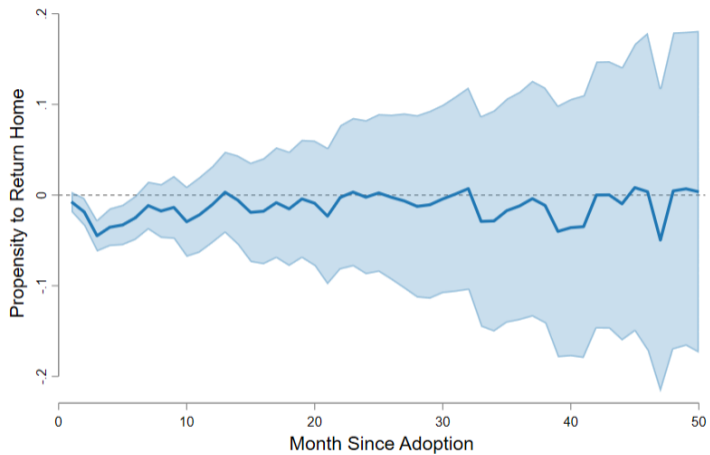
Experienced Owners

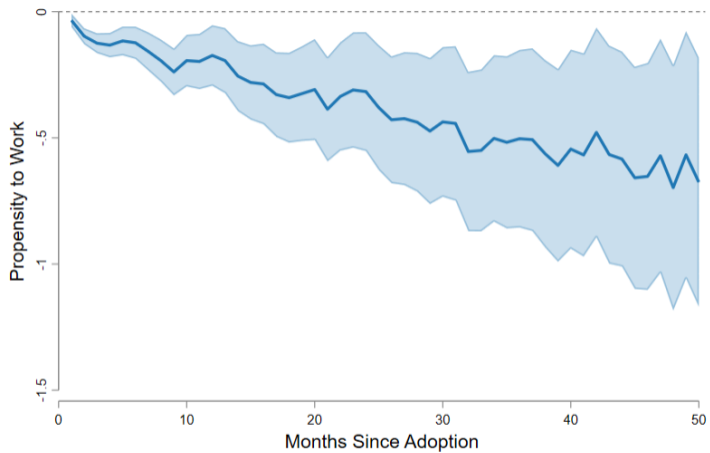


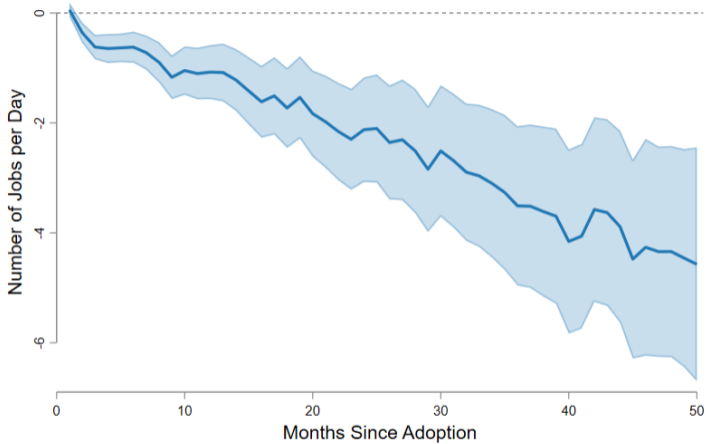
High-Confidence Home Assignment



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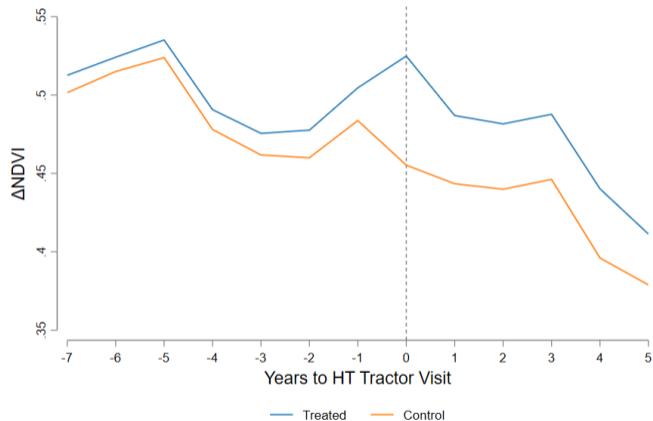
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Matching Algorithm

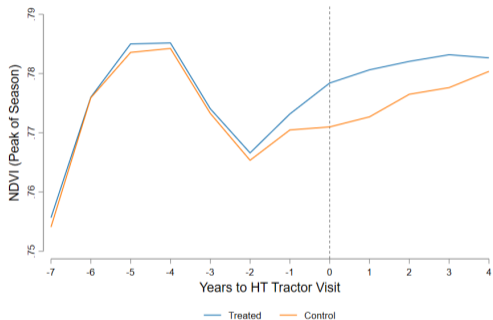
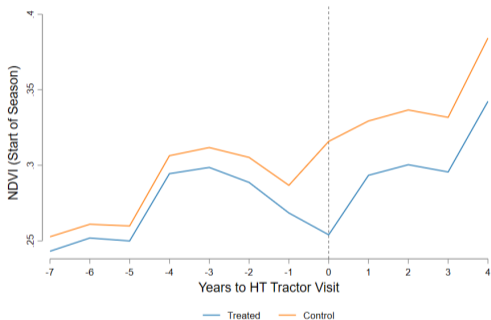
- Sample selection
 - Fields serviced in January-April (land preparation)
 - First visit only
- For each eligible job:
 1. Draw buffer of 1km around job centroid
 2. Filter buffer pixels with similar **cropland probability** ($\pm 5pp$)
 3. Polygonize contiguous pixels and filter candidates with similar **area** ($\pm 20\%$)
 4. Select polygon with most similar **pre-treatment trend in $\Delta NDVI$** based on minimizing sum of squared differences
- Other job and control polygon pixels are excluded from being selected

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Comparison of Individual Means in Raw Data

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Comparison of Individual Means in Raw Data: Separate Components


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Equilibrium

Given model parameters (θ, κ, γ) , exogenous and geographic features $(A_j, \bar{H}_j, D_{hj}, T_{-1,h})$ and \bar{T} , an equilibrium is a vector (r_j, T_j) such that:

- Tractor markets clear: for all j , the supply $T_j = \sum_h \pi_{j|h} T_{-1,h}$ is consistent with farmers' demand $r_j = \gamma A_j (T_j / \bar{H}_j)^{\gamma-1}$
- Total tractor supply is fixed: $\bar{T} = \sum_j T_j = \sum_h T_{-1,h}$

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